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Testing a new approach to construct international financial market indices: An application to Asian-Pacific economies

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Thesis submitted for the degree of PhD

January 2017

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Declaration for SOAS PhD thesis

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Abstract

The import price is conventionally predicted mainly by world trade price and other trade-related variables in macro-econometric models. This thesis seeks to enhance the predictive power of those models through explicit inclusion of the financial market information. The task entails construction of external Financial Condition Indices (FCIs). Import price indices of six Asian-Pacific economies—Singapore (SG), Korea (KOR), Taiwan (TW) , Thailand (TH), Indonesia (ID), and Malaysia (MA) are modelled in this research experiment. The external FCIs are aggregated from high-dimensional financial indicators, which are selected to represent markets of developed economies—US, Europe, UK, and Japan. Monthly data for the period of 1991M1–2013M9 are used. In addition to predictive power, two other goals are also targeted during the experiment: stability of indicator weights during regular data updates, and economic interpretability of FCIs.

The thesis starts construction of FCIs by following the widely adopted Principal Component Analysis (PCA), based on the Dynamic Factor Model approach (PCA–DFM). Two weaknesses of PCA–DFM are noticed: (1) indicators weights are unstable and given a single set of external financial indicators, and (2) the resulting FCIs are identical to all six economies. Some improvement in the predictive power is observable, but marginal and inconclusive with respect to all six economies. Subsequently, the thesis explores the Partial Least Squares (PLS) approach in three parts: (1) PLS regression method to construct economic-specific FCIs; (b) Simple Dynamic Sparse PLS method (SDS–PLS) to relax the dynamic, synchronised restriction among all indicators in both PCA–DFM and PLS regression; and (3) Revised Dynamic Sparse PLS method (RDS–PLS), which replaces the reflective mode in SDS–PLS by the formative mode.

In order to examine weight stability of indicators, FCIs are also concatenated. Once the predictive power of concatenated FCIs is established, economic interpretability of individual indicators, especially those with stable weights, are investigated.

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A special thanks to my parents. Words cannot express how grateful I am to my mother and father for all of the sacrifices that they have made on my behalf. Their prayers for me have sustained me thus far. I would also like to thank all of my friends who supported me in writing, and motivated me to strive towards my goal. And finally, I would like express appreciation to my beloved partner Fan Yang who spent sleepless nights with and was always my support in the moments when there was no one to answer my queries.

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Chapter 1 Introduction

This chapter explains the rationale for the research of this thesis in five sections. Section 1.1 reviews the literature of Financial Condition Indexes (FCIs), which leads to the discussion of the theme and the main contribution of this thesis: in searching for international FCIs external to a number of Asian-Pacific economies, the commonly used method of estimation, the Principal Component Analysis or its augmented form, the Dynamic Factor Model (PCA–DFM), was found to be problematic, because it does not reflect the characteristics of a target economy; this is exactly the problem investigated in this thesis, because the six economies examined are developing at distinctively different stages.

Section 1.2 then shows that the degree of openness of the six economies, especially with respect to the policies concerning foreign exchange and capital control, are key to the success of an international FCI. Through a brief introduction of a new method—Partial Least Squares (PLS), Section 1.3 shows that international FCIs, estimated by PLS, can be useful alternatives, because PLS uses the target variable to customize the weight estimation, while the DFM cannot; the section also notes that even though there are a few economic studies using PLS, they have not been used in the context of this thesis. Section 1.4 further highlights the practicality issue existing in the literature of FCIs. Finally, Section 1.5 summarizes major contributions, experimental designs, and the organization of this thesis.

1.1 Literature review of FCIs

World economies have seen recessions after the 2008 US-led financial crisis (henceforth, the 2008 crisis), but it has been widely argued that macroeconometric models failed to predict this crisis. There is an increasing literature that has discussed the failure of macroeconomics in modelling financial conditions following the 2008 crisis, such as Herrmann and Mihaljek (2010); Borio (2011); Borio et al. (2013); Galati and Moessner (2013); Borio (2014); Borio, Disyatat and Juselius (2014); Furlanetto, Ravazzolo and Sarferaz (2014); Ollivaud and Turner (2015). Among others, Galati and Moessner (2013) surveyed the literature on macroprudential analysis.[1] They questioned the commonly used approaches, namely that dynamic stochastic general equilibrium models and macro stress testing models cannot sufficiently model the impact of financial shocks on the macro economy. C. Borio (2014) also recognized that economists have not tried very hard to incorporate financial factors into standard macroeconomic models. The mismeas-

[1] In the current context, it can be understood as macroeconomics modelling of financial conditions.

urement of the impact of financial conditions on the real sector therefore prevents agents, namely households, firms, and governments, from correctly assessing the systematic risk, or more specifically, from anticipating the fluctuation of the macro economy caused by financial innovations.

Among others, an influential study by Hatzius et al. (2010) pointed out that a newly developed Financial Conditions Index (FCI), which was defined as an aggregate of financial variables containing 'the information about the future state of the economy', could help predict three key macroeconomic variables—the GDP growth rate, industrial production, and inflation. After their paper, the literature on using FCIs to predict the macro economy became abundant, with other studies reporting similar findings, such as Brave and Butters (2011); Osario et al. (2011); Matheson (2012); Tng et al. (2012); Debuque-Gonzales and Gochoco-Bautista (2013); Angelopoulou et al. (2014); and Darracq Paries et al. (2014). Inspired by the largely enriched literature on FCIs in the post–2008 crisis period, it is the main task of this thesis to construct FCIs that can contribute extra predictive power to macroeconometric modelling.

In these papers, the FCIs and the target macro variable are from same economy and, therefore, cannot explain how FCIs constructed from worldwide financial indicators affect an open economy. For brevity and clarity, this chapter shall refer such FCIs as international FCIs and previous ones as domestic FCIs. For central banks of open economies, international FCIs can provide useful leading information for domestic economies, and monetary policies can be set accordingly.[2] There are a few studies that seek to construct International FCIs. For example, Gumata, Klein and Ndou (2012); Qin and He (2012); and Ho and Lu (2013), respectively, construct international FCIs with respect to South Africa, China, and Poland.

Like domestic FCIs, the international FCIs in the literature use the same methodology to estimate weights—PCA–DFM. According to (Stock and Watson 2011, 2), DFM is 'a time-series extension of factor models previously developed for cross-sectional data', and forecasters get the benefit of using a large number of variables by using a small number of DFM factors, given that some conditions are met.[3] The use of DFM in economic research can be traced back to the practice of modelling business cycles. DFM was first proposed by Geweke (1976), and Sargent and Sims (1977) published early influential empirical work. Specifically, upon realizing that a priori restrictions on large-scale macro econometric models may not be reliable, Sargent and Sims (1977) used DFM to estimate one common factor that could model the business cycle. As

[2]For example, Kose et al. (2003) and Ciccarelli and Mojon (2010) found that there is a common world component that explains the global inflation, because of increasing import volume.
[3] This thesis reports the conditions in Chapter 2.

a result, they found that the common factor could explain a large fraction of the variance of many macroeconomic series. The application of DFM methodology in macroeconomics modelling was then largely pushed by J. H. Stock and M. W. Watson.[4] (henceforth, S-W) who improved DFM by estimating factor(s) more directly, and therefore, facilitating the interpretation of factor(s); see Engle and Watson (1981) for a discussion of the comparative advantages of the S-W DFM method. A vast literature, including Engle and Watson 1981; Watson and Kraft 1984; Stock and Watson 1989; (Stock and Watson 1998; Stock and Watson 2002; Kose et al. 2003; Giannone et al. 2005; Stock and Watson 2006, consistently found that the S-W DFM[5] could be useful for macroeconomics modelling, especially with respect to short-term forecasting. For example, Stock and Watson (1989, 391) concluded that 'the single-index model imposes restrictions on the joint time series properties... that are not rejected by the data'. It is noteworthy that in their conclusion, the 'single-index' is estimated by the S-W DFM method and the 'restriction on the joint time series properties' is the co-movement of the joint time series. In summary, the confidence in the S-W DFM method was gradually built up in empirical business cycle analysis, until it was first used to estimate an FCI in Hatzius et al. (2010).

Among the several studies on international FCIs, Qin and He (2012) is worth highlighting. They constructed an international FCI external to China and tested the predictive power of their FCI on four macro variables—the total exports, M1, import price index, and market interest rate. Following their research focus, this thesis seeks to construct international FCIs corresponding to six Asian-Pacific economies—Singapore, Korea, Taiwan, Thailand, Indonesia and Malaysia—and test the predictive power of these international FCIs on the import price index of the six target economies. The import price index is selected, instead of GDP, as the main target variable for two reasons. First, in mainstream macro econometric models, GDP is derived from components of the national account, e.g., consumption, capital formation, and net foreign trade if the models are built from the expenditure side. Second, the import price index is inadequately modelled in macroeconomics practice. In macroeconomics modelling practice, the import price index is normally either treated as exogenous or modelled by a trade-weighting world export price, while the impact from external financial markets is ignored. Since, in theory, the import price index should be susceptible to external financial markets because of its close linkage to the world economy, an international FCI is likely to contribute to the prediction of import price index. This is especially the case for an economy with a large foreign sector,

[4] M. W. Watson is also the co-author of Hatzius et al. (2010).
[5] As I shall argue in Chapter 3, the S-W DFM FCI is similar to the PCA FCI, so the general comment at the beginning of this paragraph, 'PCA or its augmented DFM' is appropriate for both types.

as Qin and He (2012) showed that an international FCI could significantly improve the prediction of the import price index of China, an export-oriented economy with large a foreign trade sector.[6]

Yet, there is a crucial issue that Qin and He (2012) did not recognize, which is highlighted in this thesis through the experimental design. In testing the predictive power of an international FCI on multiple target economies, PCA–DFM assumes the indiscriminate entry of financial indicators, without regard to the characteristics of different target economies, and therefore, the chance is high that the resulting international FCI has only limited predictive power as to some target economies, and even provides noise rather than signal information as to other target economies—an issue does not exists in Qin and He (2012) because they only target one economy.

1.2 Economic background of the six target economies

The international FCI estimated by PCA–DFM, therefore, is unlikely to improve predictions for all six economies in this thesis. These economies are selected primarily because they are small, open, export-oriented economies with large foreign trade sectors. As argued before, these economies are likely to see their import price index improved by an international FCI. In addition, the large share of foreign trade sector of these six economies implies that the domestic inflation, a key variable of the monetary policy that the central banks target, can be significantly affected by the inflation of the import price index. However, the six economies are at different stages of economic development and are exposed to the world economy to different degrees. These differences are worth elaborating on in this section, because they largely imply the failure of the PCA–DFM FCI. A new method that can reflect these differences in constructing the international FCI will be introduced in the next section.

As to economic development, Singapore, Korea, and Taiwan belong to newly industrialized economies, while the remaining three are still developing economies; see ADB (2009). As to their foreign trade sectors, they all contribute a large share to their respective domestic economies, but vary significantly. From Figure 1.1, Singapore heavily relies on the foreign trade sector, with its trade openness index amounting to over 120 percent, while Indonesia is least open, with its trade openness index reaching just above 40 percent.

[6] It is worth noting that they did not test the predictive power of the international FCI based on a macroeconomics model. This argument shall be elaborated in Chapter 2.

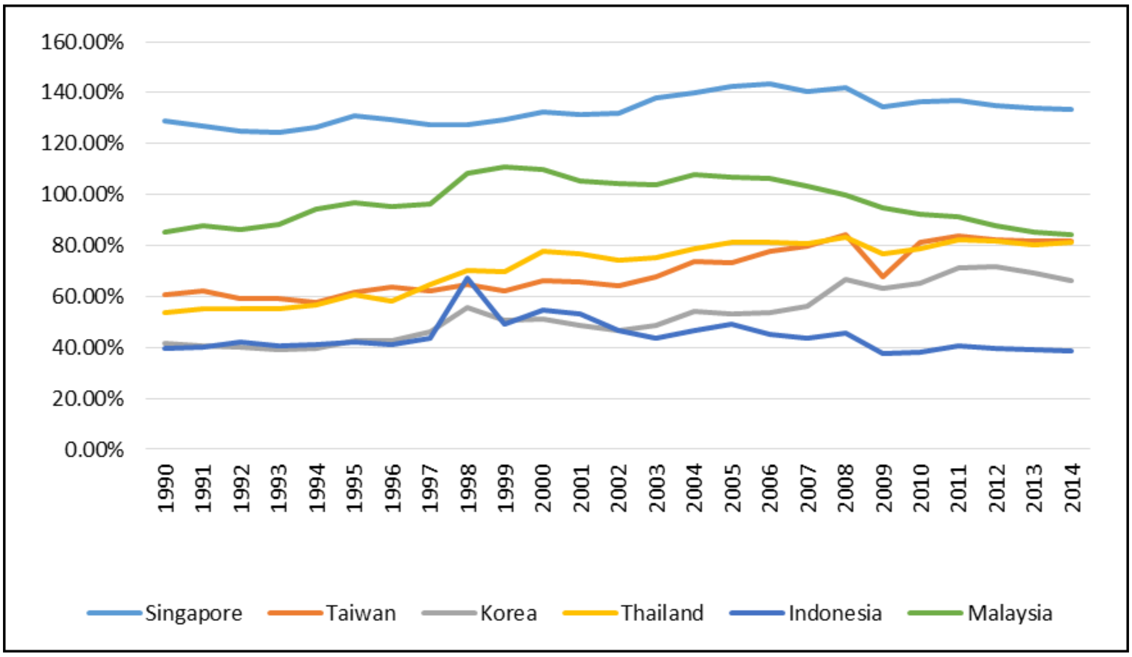

Figure 1.1 Trade Openness Index of six target economies

Note: The formula used to calculate the openness index is $\frac{Imports+Exports}{GDP+Imports}$. All data are collected from UK data service: stats.ukdataservice.ac.uk/.

Beyond the openness of their trade sector, a further introduction to their individual financial systems is necessary, because a more financially open economy also implies a significant pass-through of external financial markets into domestic economy and vice versa. The following subsections focus on the policies of foreign exchange rate and capital flow, as they are used in the literature to evaluate the degree of openness of financial systems; see Lane and Milesi-Ferretti (2007) and Chinn and Ito (2008).

Singapore

Singapore is a small city-state economy and a financial centre in Southeast Asia. As noted by Huat et al. (2004); Chowdhury (2007); and Lin et al. (2013), its fast-growing financial services rely heavily on external economies. In 2003, it had one of the highest inward foreign direct investments (FDI)[7] and around one-third of the FDI flows into financial services. In addition to large-scale financial services, almost all forms of controls on foreign exchange restrictions and capital flows were abolished in 1978. The Monetary Authority of Singapore (MAS) uses the exchange rate, instead of the more commonly used interest rate, as a counter-cyclical policy tool. In order to drive out currency speculation in the Asian Currency Crisis (ACC) and prevent

[7] According to Chow (2010), the size of total imports and exports has been approximately three times that of GDP over the past three decades.

the Singapore Dollar market-driven depreciation, MAS widened the boundaries of the policy band, i.e., the adjustment of exchange rate; see Chow (2010). Following the ACC, a managed floating policy was adopted by managing the exchange rate with an undisclosed band against various currencies. In terms of capital control, MAS monitors the balance of internal and external macroeconomics, rather than capital flow directly. In this regard, Singapore is at risk for sudden shifts in capital flows. In summary, Singapore's experience with capital flows after the ACC has been benign; a related supervisory regulatory framework has yet to be built and, therefore, Singapore is under the threat of an external financial shock; see Chow and Kriz (2007).

Korea

Korea liberalized and opened its financial markets in early 1990s. According to Kim and Yang (2010), the liberalization of its capital accounts started from 1980s and was strengthened when it joined the Organisation for Economic Co-operation and Development (OECD) in 1996. In the ACC, Korea was forced to depreciate its currency, and by accepting the International Monetary Fund (IMF) conditions, Korea took further steps towards bold liberalization of its capital account. The money market and real estate market were completely opened to foreign investors by the end of 1997. Along with the liberalization of capital markets, the foreign exchange was relaxed—a free-floating exchange rate system was adopted following the ACC. A vast literature was also found that examines why Korea suffered significantly from the 2008 crisis. Kim and Yang (2010) argued that a lack of control on capital inflows caused a bubble in the domestic stock market in 2006–7. Kim and Rhee (2009) pointed out that Korea is susceptible to large exchange rate instabilities because of its freely fluctuating exchange rates. ADB (2009) noticed that a banking statistic for Korea, the loan-to-deposit ratio, was significantly above 1, which is noticeably higher than the other target economies. In a word, Korea lacked control of short-term capital inflow during 2008 crisis.

Taiwan

Taiwan started its globalization process in the late 1980s. In 1987, Taiwan liberalized controls on its current account transactions and allowed the new Taiwan Dollar to float, basically free, against US Dollar in 1989; see Glick and Hutchison (2007). The liberalization process has been slow. According to Liu and Hsu (2006, 671), although the exchange rate is occasionally controlled by the central bank, 'the foreign exchange control on the current account was totally abolished and restrictions on capital movement has also relaxed significantly since

2004'. In the wake of the 2008 crisis, it took a range of measures to reduce the speculation in its foreign exchange market following the crisis, with only mixed results as to whether Taiwan successfully controlled the capital flow. Pradhan et al. (2011) found the measure to limit domestic banks to providing liquidity to non-deliverable forward markets has had little impact on the behaviour of the currency, while Gallagher et al. (2011) empirically showed that Taiwan has controlled the currency bubble more effectively than Korea.

Thailand

According to Leightner and Lovell (1998), Thailand liberalized its financial system at the beginning of 1990s. Due to the great capital account deregulation, especially the deregulation on short-term borrowing, with high interest rate differential, huge capital inflows were observed before the ACC. When this capital fled during the ACC, the Baht was forced to float[8] and was hugely depreciated. From then on, Thailand employed several measures to supervise its capital accounts. It regulated the capital inflows by selecting only the less risky capital inflows, such as longer maturity loans or direct investments, and reducing short-term inflows ("hot money").[9] In addition, in 2006–7, a foreign exchange rate intervention made by the Bank of Thailand caused a build-up of foreign exchange reserves within a short time. In summary, Thailand has adopted a prudent capital control and foreign exchange policy.

Indonesia

Indonesia is an oil-rich economy. As its oil revenue declined in 1980s, the government was forced to adopt a more evenly distributed export-promotion strategy. According to Chowdhury (2007), the restrictive foreign investment regime was largely liberalized in mid-1980s, along with some deregulations in the financial sector, such as the granting of permission for foreign banks to settle outside of Jakarta. These measures resulted in a rapid expansion of the banking sector, although it was slower than for the other target economies. However, the massive scale of corruption has damaged confidence in the government, and the growth rate of capital inflow has been below other Asian economies. In the wake of the ACC, and especially with the currency depreciation of Thailand, Malaysia, and the Philippines, the Indonesian Rupiah could not peg to US Dollars and was depreciated significantly. Learning lessons from the ACC, the government of Indonesia tightened regulations and supervision of the banking sector. Additionally, although capital inflow rebounded following the ACC, its scale is still below the

[8] It was pegged to US Dollars.
[9] See Sangsubhan (2010).

average for Asian economies.[10] Due to these two facts, Indonesia is not largely exposed to banks in the US, EU, or Japan and avoids large credit exposures to subprime loans and securities in the US.

Malaysia

The Malaysian economy grew rapidly in the 1990s, driven by the influx of FDI from Japan and the US; see Chowdhury (2007). Prior to the 2008 crisis, a managed floating foreign exchange rate policy was used. When the ACC occurred, Malaysia fixed the Ringgit to the US Dollar and imposed controls on capital flows, especially capital outflows.[11] The fixed exchange rate policy was maintained until 2005, when a managed floating exchange rate policy was re-adopted. According to Foong (2008), the large capital inflow, combined with current account surplus, have exerted upward pressure on the exchange rate. The monetary authority has intervened in the foreign exchange market and used both prudential lending procedures and fiscal policy to control capital inflows. In summary, Malaysia has adopted a prudent foreign exchange policy and rigidly controls its capital account.

1.3 A brief introduction of Partial Least Squares

As shown in last two sections, the six target economies vary significantly in terms of their economic development and openness to world economies, and, therefore, a new method that can reflect the characteristics of each target economy is needed. In this thesis, Partial Least Squares (PLS) is proposed to estimate international economic-specific FCIs, one FCI for each target economy, as an alternative to PCA–DFM.

As historically reviewed by Sanchez (2013), in the pre-PLS era, Herman Wold developed an iterative least squares algorithm that could be used for PCA, factor analysis, interdependent systems, etc., in the 1960s. Herman Wold’s endeavour to distinguish recursive systems vs. interdependent systems, which PCA and factor analysis rest upon, led to the extension of his iterative least squares to the recursive systems. PLS, a covariance-based method that rests upon recursive systems, was first proposed in 1966; see Wold (1966,1974); . It developed in the 1970s along with canonical correlation. In the 1980s, PLS[12] was largely applied in chemomet-

[10] The worst investment environment among Asian economies could probably account for such small-scaled capital inflow; see Chowdhury (2007); Titiheruw and Atje (2008).
[11] See Abdelal and Alfaro (2003).
[12] It was actually the Partial Least Squares Regression methodology, which is popular in the chemometrics area. PLS Regression, together with PLS Path Modelling, are the two methodologies that belong to PLS. The introduction of these two methodologies and their differences shall be elaborated in Chapters 3, 4, and 5. A more apt name would be Partial Least Squares Path Modelling, rather than Partial Least

rics research (Wold et al. 1984) but not in economics research yet. In 1990s and early 2000s, there were a few econometric studies that used PLS to construct some customer satisfactory Indices, such as American Customer Satisfactory Index in Brecka (1994) and retailer equity indexes in Arnett et al. (2003). The unpopularity of PLS in econometrics research is largely due to a lack of user-friendly econometric software based on PLS.

The iterative least squares algorithm can be explained in simple words regarding PCA and PLS. As for PCA, iterative loops are run for one block of variables. The least square is used to estimate principal components iteratively. As to PLS, the target variable is added as a second block, and the iterative loops are run on a cross product of the two blocks. The least squares method is used to estimate principal components for both blocks iteratively. A more elaborate description of the PLS algorithm can be found in Chapter 3, so this chapter shall only highlight the differences between PLS and PCA–DFM in the context of this thesis. From the iterative least squares algorithm, it can be directly shown that PCA–DFM does not take into account the varying target economies; therefore, the FCI may contain too much irrelevant information—the noise—about a target economy; unlike PCA, PLS allows the target to customize weights from the loops on cross product. The international FCIs estimated by PLS are supervised by the target economy and, therefore, are economy-specific.

In recent literature, macroeconometric studies have been found that use PLS methodology.

Table 1.1 Macroeconometric studies using aggregated PLS factors

Economic papers	Disaggregate indicators	Target variables; target economies	Reasons why not in the area of international FCIs
Lin and Tsay (2005)	S-W datasets (Stock and Watson [2002, 2005]), that is, a mixed set of US macro and financial indicators.	US; S-W target variables (Stock and Watson [2002, 2005]), that is, inflation, industrial production, etc.	Non-international indicators; Mixed with macro indicators,
Groen and Kapetanios (2009)	S-W datasets[13]	US; S-W target variables[14]	Non-international indicators; Mixed with macro indicators.

Squares Regression. The latter was actually popular in chemometrics, owing to the son of Herman Wold, Svate Wold (see Wold et al. [2001]), while the former name was only seen in the marketing industry.

[13] Same as above and so is the case for below.

[14] Same as above and so is the case for below.

Eickmeier and Ng (2011)	Amixed set of international macro and financial indicators	New Zealand; GDP growth rate	Mixed with macro indicators
Fuentes et al. (2014)	S-W data sets	US; S-W target variables	Non-international indicators; Mixed with macro indicators
Lannsjö (2014)	A mixed set of macro and financial indicators from OECD economies	OECD economies; Industrial Production Index	Mixed with macro indicators
Fuentes de Díaz (2015)	S-W datasets	US; S-W target variables	Non-international indicators; Mixed with macro indicators
Kapetanios et al. (2015)	A set of US financial indicators	US; GDP growth rate	Non-international indicators
Giglio et al. (2016)	A mixed set of macro and financial indicators from UK, US, and Euro area.	US; growth rate of Industrial Production	Mixed with macro indicators

The papers listed in Table 1.1 all found that PLS factors have superior predictive power, especially against PCA factors,[15] that is, empirical findings corresponding to the previous theoretical argument of PLS vs PCA. However, these pioneering studies do not target the Asian-Pacific economies that this thesis selects to predict, nor are they in the area of international FCIs. Specifically, the three studies that intended to model the international impac—Eickmeier and Ng (2011); Lannsjö (2014); and Giglio et al. (2016)—had their PLS factors aggregated from a mixed set of macro and financial indicators. In fact, only Kapetanios et al. (2015, highlighted by bold borders in the table) isolated financial indicators from macro indicators, but their FCIs are domestic, regarding the US.

1.4 Difficulty in disaggregate economic interpretation in FCIs literature

The difficulty in disaggregate economic interpretation of FCIs has commonly existed in literature, along with the methodological issue of PCA–DFM already discussed. Hatzius et al. (2010) recognized that the much diversified transmission channels from various financial instruments to the macro economy would keep changing over time. Therefore, they assumed non-constant

[15] In fact, among these studies only Lin and Tsay (2005) did not compare PLS factors with PCA factors.

weights estimated by PCA–DFM. Based on the non-constant weight estimates, they proposed that the aggregate PCA–DFM factors are constant, as the non-constancy at the disaggregate level is averaged at the aggregate level. In the belief that the aggregate FCIs are time-invariant, they tested the predictive power of FCIs in an *ex post* context.

In addition to the non-constancy of weight estimates, this thesis, however, argues that FCIs were unlikely to be constant during the 2008 crisis, given its unprecedented scale and depth. In this sense, a predictive test of *ex ante* FCIs is needed. Two studies discussed the forecasting performance of *ex ante* FCIs and found that it was not guaranteed that *ex ante* FCIs have the same positive predictive power as *ex post* FCIs. Specifically, Koop and Korobilis (2014) surveyed the existing literature regarding *ex post* FCIs and noticed that some financial indicators were selected because of their pronounced fluctuations during 2008 crisis. The survey of Aramonte, et al. (2013) showed that the predictive power of the *ex post* FCI was weak, unless the financial crisis was included.

Further and more importantly, the comments of Dudley (2010) on FCIs constructed by Hatzius et al. (2010) highlighted that since their FCIs are time-varying, weighted (presumed) averages of a large number of variables,[16] it is difficult to update and increase the understanding of dis-aggregate transmission channels from financial markets to the macro economy. In order to carry out the disaggregate analysis, this thesis seeks to construct FCIs with its weights fixed at least for a period, and its out-of-sample forecasting performance used as a statistical criterion to check whether the predictive information content is maintained in the fixed-weighted FCIs.

1.5 Main contributions and structure of this thesis

Corresponding to the several research gaps found both in the literature and in the research process of this thesis, four major contributions are listed following the chapter order:[17]

1) A more rigorous specification of a benchmark-forecasting model than what was used in most of the FCI literature is proposed as the base to evaluate the predictive power of international FCIs.
2) A FCI is constructed by an innovative method—PLS. The various economic-specific FCIs, corresponding to various target economies,[18] are tested against the PCA-based FCIs without the target.

[16] His argument applies to other FCIs in the literature, as similar FCIs were constructed in the literature.
[17] The two contributions mentioned above are included. Four contributions are arranged to follow the flow of this thesis.
[18] In Chapter 3, PLS FCIs are constructed for all six target economies.

3) PLS FCIs, with weights regularly updated, are constructed and evaluated, both in terms of aggregate and disaggregate predictive power.
4) Regarding PLS-based FCIs, an investigation of the leading role of financial indicators at the disaggregate level is carried out.

1.5.1 Experimental design

- An FCI(s) is mode-based constructed, and the predictive power of FCI(s) is also model-based, evaluated by comparing a mean squared forecasting error (MSFE) of two forecasting models, such as comparing the MSFE of two types of FCI(s) forecasting models—FCI(s) constructed by PLS and PCA, or by comparing the MSFE between the FCI(s) forecasting model and a benchmark model without FCI.
- Sample data ranging from 1991M1 through 2013M9, namely the 2008 crisis period is included for out-of-sample evaluation.
- The benchmark model includes trade-related variables as explanatory variables that are normally used in macroeconometric models.
- Two modifications on PLS methodology are proposed to model disaggregate dynamics more meticulously—Simple Dynamic Sparse and Revised Dynamic Sparse methods. To what extent financial indicators lead the target variable can be evaluated when these two modified PLS methods are used to construct the FCI.

1.5.2 Organization of the thesis

The organization of rest of this thesis is illustrated in Figure 1.2.

- Chapter 2 carries out the predictive test of an *ex ante* FCI constructed by DFM vs. a benchmark model during 2008 crisis.
- Based on the construction method in Chapter 2, Chapter 3 carries out the predictive test of PLS FCIs vs. both PCA FCI and the benchmark model, investigating the predictive power of financial indicators in terms of the PLS FCIs. Disaggregate contribution through weight estimates are also investigated in this chapter.
- The PLS FCIs constructed in Chapter 4 are modified by Simple Dynamic Sparse (SDS) and allow for updating of weights. Chapter 4 then carries out the predictive test of SDS–FCIs vs. PCA, PLS, and the benchmark model used in Chapters 2 and 3. It is noteworthy that the Simple Dynamic Sparse PLS FCIs are allowed to have their weights updated on an annual basis, and, therefore, both the constancy of weights and the lag estimates, that is, the leading role of various financial indicators, can be evaluated.

- Chapter 5 move one step further beyond Chapter 4 in comparing the predictive power of PLS FCIs modified by Revised Dynamic Sparse (RDS–PLS) vs. SDS–PLS FCIs and further compare the findings on the disaggregated dynamic forms regarding RDS–PLS FCIs with those from SDS–PLS FCIs.

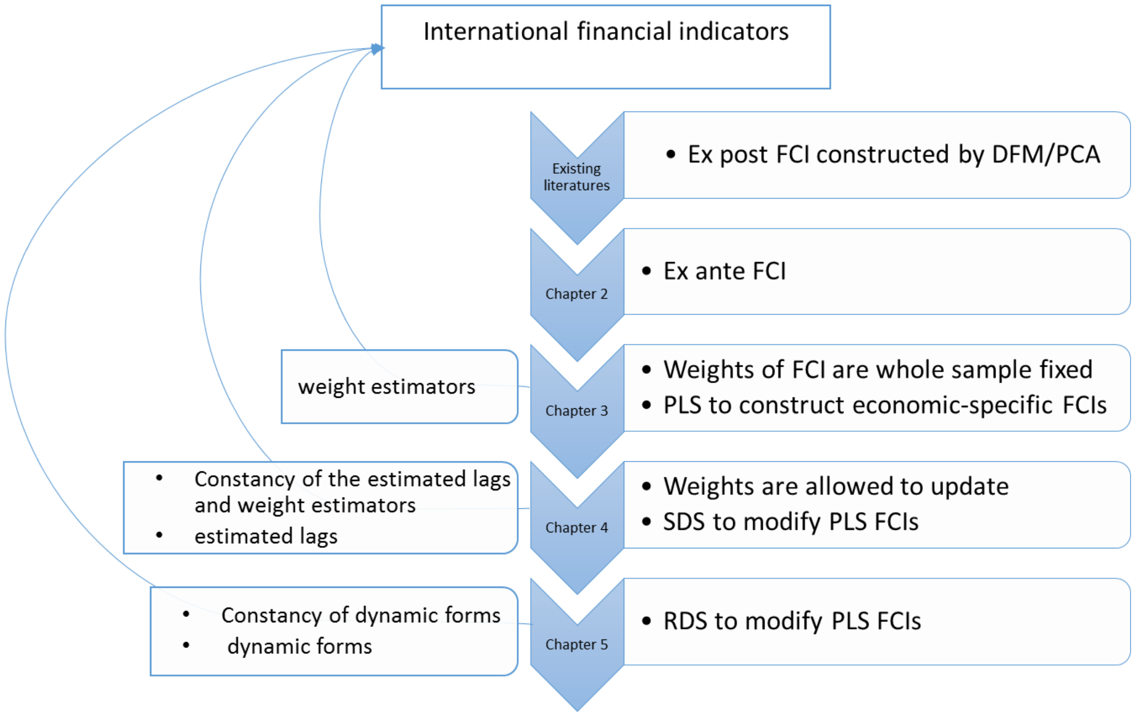

Figure 1.2 Flow of chapters of this thesis

Chapter 2 An Experiment on the FCIs of Qin and He

2.1 Introduction

This chapter seeks to extend the research line by Qin and He (2012) (henceforth, QH) in testing (1) the predictive power of international FCIs proposed by QH in forecasting the import price index of six Asian-Pacific economies—Singapore, Korea, Taiwan, Thailand, Indonesia and Malaysia, and (2) whether QH's FCIs aggregated from pre-classified financial indicators have better forecasting performance.

2.1.1 QH's experimental design w.r.t the selection of international FCIs and pre-classification method

QH's chosen financial variables are extracted from advanced economies, that is, Japan, the US, the UK, and the Euro Area, at a monthly frequency. The financial variables cover the banking sector, commodity price, equity markets, fixed-income markets, and futures and option markets, etc. A brief list of these financial variables can be found in Appendix 2A[20] and a detailed list can be found in Appendix 3 of QH. Since in factor analysis, a factor is required to be aggregated from stationary time-series data, these financial variables are transformed into stationary financial indicators. In the transformation process, however, QH were shrewdly aware that indicators of distinctively different dynamic properties were generated, which is a phenomenon largely neglected in the previous literature. Taking two commonly used (stationary) financial indicators (in FCIs literature) as an example, distinctively different dynamics between two financial indicators, TED spread and monthly growth rate of the US short-term interest rate, are shown in Figure 2.1. TED spread, as a spread between two financial variables—the short-term interest rate of the money market net of the risk-free rate, has slow dynamics. By contrast, the monthly growth rate of the short-term market interest rate has a much higher frequency. In order to differentiate financial indicators according to the difference in their frequency, QH termed those cross-variable, transformed financial indicators (spread or ratio of two or more financial variables), which have quite slow dynamics, as long-run indicators, and pointed out that they measure the 'disparities between different markets and sectors pertinent to the cross-variable comparison' (p.7); they termed the other temporally transformed indicators, which have higher frequency than the previous long-run indicators, as short-run in-

[20] A few financial variables are not used because the database (that they are collected from) are not publicly accessible. It should not result in a significant difference in constructing FCIs, given the large data set.

dicators. These short-run indicators were further subdivided by QH into monthly (by difference or proportion), quarterly, and an annual short-run indicator set because the frequency of these three sets of short-run indicators follow a descending order.

In doing so, QH argued that long-run indicators had more predictive information due to a dynamic match between them and macro targets, while short-run indicators that were too fast in terms of dynamics caused a 'dynamic mismatch between financial indicators and the real-sector variables'. Additionally, QH argued that FCIs aggregated from a mixed set of long-run and short-run indicators (henceforth, mixed FCIs) are dominated by low-frequency (slow dynamics) information at the expense of high-frequency information; and FCIs will be less dominated by low-frequency information if long-run indicators are mixed with short-run indicators that are temporally transformed with a long time-span. For example, FCIs aggregated from a mixed set of annual short-run and long-run indicators are more likely to reflect short-run information (that of annual short-run indicators), compared to FCIs aggregated from a mixed set of monthly short-run and long-run indicators.

Two types of FCIs were constructed by QH in order to test the information loss when long-run and short-run indicators are mixed together. For brevity, QH used separated FCIs to denote FCIs aggregated from four separated sets—long-run, monthly, quarterly, and annual short-run indicators; and used mixed FCIs to denote FCIs aggregated from three mixed sets—long-run indicators mixed with monthly short-run (henceforth, monthly mixed FCIs), with quarterly short-run (henceforth, quarterly mixed FCIs), and with annual short-run indicators (henceforth, annual mixed FCIs). Then a predictive test of separated FCIs' forecasting model vs. mixed FCIs' forecasting model was carried out in order to find whether a pre-classification can improve the prediction; see Equations (3a) and (3b) in Qin and He (2012, 13).

2.1.2 A brief introduction of modified experimental design based on QH

This chapter is organized as follows. Section 2.2 introduces the experimental design adopted in this thesis with particular focus on the two modifications described in Section 2.1.1. Section 2.3 compares the forecasting performance of separated FCIs, mixed FCIs, and the benchmark forecasting model for each target economy. Section 2.4 concludes with main findings.

2.2 Experimental design

This section explains the experimental design with particular focus on the two modified experimental designs—the construction of *ex ante* FCIs and the specification of both benchmark and FCIs' forecasting models, which include trade-related macro predictors.

2.2.1 The construction of *ex ante* FCIs

The in-sample data are set at 1991M1–2008M4 while subsample 2008M5–2013M9 is left for out-of-sample evaluation. FCIs are in-sample estimated by DFM, the same methodology as that in QH. The estimation of FCIs by DFM can be expressed in the following matrix form (Stock and Watson 2011).

$$X_t = \mathrm{A} f_t + \mu_t \tag{2.1}$$

$$f_t = \mathrm{B}(L) f_{t-1} + \nu_t \tag{2.2}$$

In Equations (2.1) and (2.2), $X_t = (x_{1,t}, x_{2,t}, \cdots x_{N,t})'$ is a financial indicator matrix composed of N standardized financial indicators. In this study it can be any of four separated sets and three mixed sets to estimate separated FCIs and mixed FCIs. A common factor matrix, $f_t = (f_{1,t}, f_{2,t}, \cdots f_{R,t})'$, is composed of R common factors. In this study FCIs of different dynamics are individually estimated by DFM. In the following analysis, $f_{lr}, f_{sm}, f_{sq}, f_{sy}$, respectively, denotes separated FCIs aggregated from long-run, monthly short-run, quarterly short-run, and annual short-run indicator sets and f_{mm}, f_{mq}, f_{my} , respectively, denotes monthly mixed FCIs, quarterly mixed FCIs and annual mixed FCIs.[23] A in Equation (2.1) is the matrix of factor loadings. $\mathrm{B}(L)$ in Equation (2.2) is the lag polynomial coefficient matrix when f_t is regressed on its own lags, and μ_t and ν_t are idiosyncratic vectors.

The number and lag length of factors, namely A and $\mathrm{B}(L)$, respectively, in Equations (2.1) and (2.2), need to be determined first. The number of factors in this chapter are determined by the criteria proposed by Onatski (2009). The lag length of factors in Equation (2.2) is determined after a full consideration of AIC,[24] SIC,[25] log-likelihood and Hannan-Quinn information criteria. From Table 2.1, the determined number of factors and lag length are similar to those of QH. Once the number and lag length of factors are determined, factor loadings (A) and factors (f_t) in Equation (2.1) are initially estimated by PCA (see Chapter 1) through balanced subsample data, then the Kalman filter method is used to deal with the unbalanced (jagged edge) full sample data, and final factors and factor loadings are obtained. (Stock and Watson 2011, 13–15)

[23] They are all individually estimated by DFM.
[24] Acronym for Akaike information criterion.
[25] Acronym for Schwarz information criterion.

The theoretical postulation on the non-constancy of factors is empirically supported here. Figure 2.2 shows that the subsample-estimated long-run FCIs are distinctively different from full sample-estimated long-run FCIs.

Because of such significant non-constancy, testing the forecasting performance of *ex ante* FCIs, instead of *ex post* FCIs, is necessary. Forecasting the FCIs, as is required in an *ex ante* context, by a simple AR model, however, indicates a loss of information. Specifically, when using the Equation (2.2) to forecast the out-of-sample part of FCIs, too much information at the indicator level is wasted because observations of financial indicators are gradually available *ex ante* in the process of a (out-of-sample) predictive test of 5 years.

The issue of loss of predictive information can be solved by a recursive estimated and forecasted method. By first highlighting how disaggregate predictive information is lost in a 12-months hence predictive test, Exhibit 2.1 intuitively explains how DFM FCIs are re-estimated and re-forecasted in this chapter.

In a 12-month ahead predictive test, the first forecasted value of FCIs at 09M4 is compared with the corresponding actual value, then the recursively forecasted value at 09M5, and so forth. In this recursively forecasting process, observations of financial indicators (X_t) at 08M5, 08M6 are gradually *ex ante* available. In order to incorporate this *ex ante* information, factors are allowed to be recursively estimated at 08M5 and 08M6.

Since FCIs (DFM factors) are non-constant, the in-sample part (91M1–08M4) of FCIs varies along with the recursive estimation process. In this sense, the FCIs' forecasting models (to forecast import price index) that are in-sample estimated are needed to be recursively estimated as well. In order to avoid such a large amount of computational work, this chapter manually fixes the in-sample part of FCIs, while allowing the out-of-sample part of FCIs to vary. As Exhibit 2.1 shows, in the second recursion, FCIs during 91M1–08M4 are held fixed like those in the first recursion (FCI_{HE}^{1}), while the newly available *ex ante* information is only allowed to update FCIs at 08M5 (FCI_{IE}^{2}). The out-of-sample forecasted[26] FCIs are based on all available *ex ante* data ranging from 91M1 through 08M5 (FCI_{OF}^{2}).

[26] They are forecast by dynamic DFM forecasting; see Harvey (1990, 147–149)

The same process is repeated in the third recursion. FCIs during 91M1–08M5 are held fixed like those in second recursion (FCI_{IE}^{2}). And the out-of-sample forecasting FCIs are based on all available *ex ante* data ranging from 91M1 through 08M6 (FCI_{OF}^{3}).

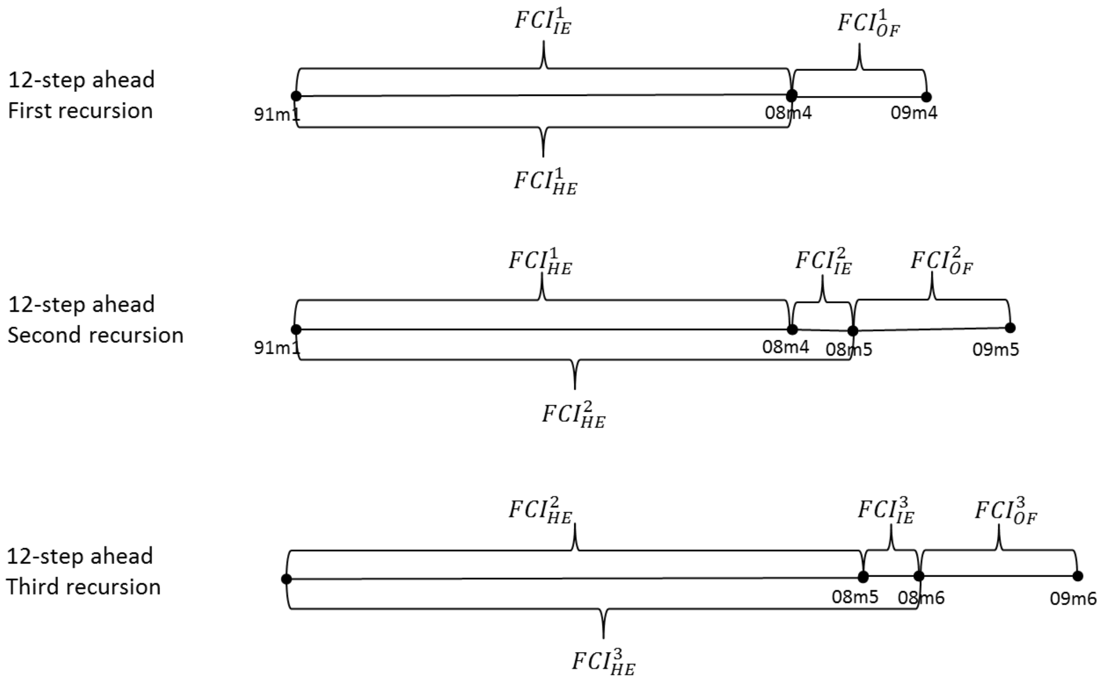

Exhibit 2.1 Construction of *ex ante* FCIs for the out-of-sample predictive test

2.2.2 Modelling import price index with macro predictors and FCIs

In theory, import price index is mainly determined by three macro variables, that is, exchange rates, producing cost of the exporters, and a mark-up set up by the exporters. In a perfectly integrated market, products will be sold for the same price everywhere, namely the law of one price holds. Therefore, the import price index should be equal to the cost of producing exports when both are measured in the same currency unit. However, Krugman (1986) pointed out that the pricing-to-market effect could cause the incomplete pass-through of exchange rate. Specifically, he found that import price of luxury automobiles from Europe (to the US) respond 'very little' to the shift of the exchange rate. This argument was then generalized by Naug and Nymoen (1996) and Goldberg and Knetter (1996). The latter argued that since factors such as transport cost, tariffs, and imperfect information will render the absolute law of one price no longer holds, the pass-through of both exchange rate and cost of producing exports are incomplete. To sum up, in an integrated market with imperfect competition, a theoretical model for the import price index can be specified as follows:

$$\mathrm{IM} = \mathrm{C} * \mathrm{ER} * \lambda \tag{2.3}$$

where C is the cost of producing exports in an exporting country's currency and ER is exchange rate, λ is the mark-up set up by the exporters and IM is the import price index in the importing country's currency. Since the mark-up, λ, reflects the competitive pressures and demand pressures in the importing country, λ can be further expressed as:

$$\lambda = (\frac{\mathrm{P}}{\mathrm{C}*\mathrm{ER}})^{\beta} \tag{2.4}$$

where P is the price of goods produced by the importing country. Substituting Equation (2.4) into (2.3):

$$\mathrm{IM} = (\mathrm{C} * \mathrm{ER})^{1-\beta} * \mathrm{P}^{\beta} \tag{2.5}$$

Taking the logarithmatic form and adding a time subscript, an econometric import price equation can be obtained.

$$\mathrm{IM}_t = (1-\hat{\beta})\mathrm{er}_t + (1-\hat{\beta})\mathrm{c}_t + \hat{\beta}\mathrm{p}_t + \epsilon_t \tag{2.6}$$

Note that the variables in lower cases stand for the logarithmic transformation.

If the estimate of $\hat{\beta}$ equals zero, the pass-through of the exchange rate is complete, that is there is no pricing-to-market effect. Otherwise, the pass-through of exchange rate is incomplete.

Despite its widespread usage in the literature on exchange rate pass-through, Equation (2.6) is over-restricted on the coefficients: (1) a unit-homogeneity in the exchange rate and competitor's prices; (2) an equal elasticity of import price index with respect to exchange rate and the cost of producing exports; and (3) a unit-homogeneity in exchange rate and competitor's price by the importing country. As shown in the literature, these three restrictions do not necessarily hold in empirical studies. (Hooper and Mann 1989; Menon 1995; Bache 2002; Sahminan 2005)

In addition to the three unnecessary restrictions, Equation (2.6) has another limitation that it is static and therefore does not have an error-correction mechanism. As a result, it could not measure the long-run pass-through of exchange rate and cost of producing exports. In addition, according to Engle and Granger (1987) and Hendry (1995), a correctly specified error-correction term can effectively incorporate the information at level into the model and increase the predictive power in the long term through feedback effect.

In order to reflect both the short-run and long-run dynamics, the above econometric model can be extended into an error correction representation:

$$\Delta \mathrm{im}_t = \hat{\alpha}\Delta \mathrm{er}_t + \hat{\beta}\Delta \mathrm{c}_t + \hat{\gamma}\Delta \mathrm{p}_t + \hat{\rho}\mathrm{ecm}_{t-1} + \epsilon_t \,, \tag{2.7}$$

where the long run error-correction term is $\mathrm{ecm}_{t-1} = \mathrm{im}_{t-1} - \hat{\alpha}'\mathrm{er}_{t-1} - \hat{\beta}'\mathrm{c}_{t-1} - \hat{\gamma}'\mathrm{p}_{t-1}$.

This thesis uses an import price in US dollars as a proxy for import price index im_t, an exchange rate of the importing country's currency unit in US dollars as a proxy for exchange rate $\Delta\mathrm{er}_t$, an export price of the importing country as a proxy for the competitor's price p_t, and a weighted average of world export price as a proxy for the cost of producing exports c_t.[31]

Modelling the import price index in US dollars is equivalent to modelling the importing country's currency in practice. In fact, modelling the import price index in the importing country's currency unit is superior against modelling the import price index in US dollars if and only if the predicted value of exchange rate is used in the econometric model. In fact, the actual value of the exchange rate is used in the literature and, therefore, by multiplying the current import price index in US dollars by the exchange rate, the import price index in the importing country's currency unit can be directly obtained without using any *ex post* information.

The pricing-to-market effect can still be interpreted when modelling the import price index in US dollars. Higgins and Klitgaard (2000) reported the finding that the import price index (in US dollars) of Korea fell below the cost of producing exports during the ACC, and postulated that the great range of locally produced alternative put more pressure on exporters to cut prices when the Korean won was depreciated.

According to Sahminan (2005), importing the country's currency unit based on US dollars can be a proxy for a theoretical exchange rate because external trades of these East Asian economies are heavily invoiced in the US dollar. As to the competitor's price, this thesis follows Cagas et al. (2006). They found that importing country's export price can be a proxy for the competitor's price and have significant explanatory power both in short run and in long run.

The world export price index, as a proxy for cost of producing exports is widely used in empirical studies; see Lord 1998; Higgins and Klitgaard 2000; Nickell 2005; Bache 2002; and Cagas et al. 2006.

[31] All macro data, including both import price index and macro predictors, are collected from the IMF database.

$$c_t = \sum_{i=1}^{20} \lambda_i p_i \tag{2.8}$$

This thesis selects 20 major (according to the relative exporting volume) exporting economies in relation to the six target economies. In Equation (2.8), λ_i is the weight of export volume of a country i; p_i represents the export price index of the country i; c_t is the resulting world export price index.

Although the coefficient restrictions on short-run variables are relaxed, two more restrictions on the coefficients with respect to the error correction term, ecm_{t-1}, are presumed or supported in the literature.

$$ecm_{t-1} = im_{t-1} - \widehat{\alpha}' er_{t-1} * c_{t-1} - (1 - \widehat{\alpha}')p_{t-1} \tag{2.9}$$

That is, from Equation (2.9), equal elasticity of the import price index with respect to the exchange rate and the cost of producing exports and long-run unit homogeneity are both assumed. As to the former, empirical studies support the equal elasticity in the long run (Naug and Nymoen 1996; Bache 2002). Moreover, both the two long-run restrictions are either presumed or supported in modelling the import price index of Asian economies (Higgins and Klitgaard 2000; Cagas et al. 2006). In these two empirical studies, world export price is directly translated into the same currency as the import price index.

As to the international FCIs, this research measures both direct and indirect predictive power of international FCIs on import price. First, an explorative empirical research is carried out to evaluate the additional predictive power of FCIs, given scarce theoretical studies on the relation between import price and international FCIs. Specifically, the modified ECM benchmark models, together with the FCI forecasting models, follow the general-to-specific approach proposed by Hendry (1995) to estimate the following final parsimonious models.

$$\Delta y_t = C_1^{\prime(L)} \Delta y_{t-1} + C_2^{\prime(L)} \Delta x_{wp,t} + C_3^{\prime(L)} \Delta x_{dp,t} + C_4^{\prime(L)} \Delta x_{er,t} + C_5^{\prime(L)} F(f_{ir,t}, f_{sm,t}, f_{sq,t}, f_{sy,t}) + \lambda \begin{pmatrix} y \\ x_{wp} \\ x_{dp} \end{pmatrix}_{t-1} + \varepsilon_t \tag{2.10a}$$

$$\Delta y_t = C_1''(L) \Delta y_{t-1} + C_2''(L) \Delta x_{wp,t} + C_3''(L) \Delta x_{dp,t} + C_4''(L) \Delta x_{er,t} + C_5''(L) F(f_{mm,t}, f_{mq,t}, f_{my,t}) + \lambda \begin{pmatrix} y \\ x_{wp} \\ x_{dp} \end{pmatrix}_{t-1} + \varepsilon_t \tag{2.10b}$$

$$\Delta y_t = C_1(L) \Delta y_{t-1} + C_2(L) \Delta x_{wp,t} + C_3(L) \Delta x_{dp,t} + C_4(L) \Delta x_{er,t} + \lambda \begin{pmatrix} y \\ x_{wp} \\ x_{dp} \end{pmatrix}_{t-1} + \varepsilon_t \tag{2.10c}$$

Here, $C_1(L), C_2(L), C_3(L), C_4(L), C_5(L), C_1'(L), C_2'(L), C_3'(L), C_4'(L), C_5'(L), C_1''(L), C_2''(L), C_3''(L), C_4''(L)$ are lag polynomial matrices; Δ is first difference; $x_{wp,t}$ refers to dollarized world export price, that is, equivalent to $\mathrm{er}_t * \mathrm{c}_t$ defined in Equation (2.9); $x_{xp,t}$ refers to domestic export price; $x_{er,t}$ refers to exchange rate; $F(f_t)$ denotes that various lagged forms of f_t that are allowed to survive in-sample, such as five-month lagged in level or one-month lagged in first difference.

In addition to the out-of-sample forecasted FCIs, the macro predictors, exchange rate, domestic export price, and world export price, are also forecasted.
They are assumed to be exogenous and forecasted by peripheral AR models, compared to the general forecasting models (2.10a), (2.10b), and (2.10c).
$x_t = C_6(L)x_{t-1}$

(2.11)In order to see the forecasting superiority among separated FCIs, mixed FCIs and the benchmark forecasting model, first a two-way[32] encompassing test is carried out.

Scenario A Given that the macro predictors for Equation (2.11); predictive tests of separated FCIs' forecasting model (Equation [2.10a]) vs. benchmark model (Equation [2.10c]); of mixed FCIs' forecasting model (Equation [2.10b]) vs. benchmark model; and of separated FCIs' forecasting model vs. mixed FCIs model are carried out.

Scenario A measures the direct predictive power of international FCIs in the sense that international FCIs are tested for their incremental predictive power in addition to macro predictors. By contrast, the evaluation of the indirect predictive power of FCIs is also carried out.

$$\Delta x_{wp,t} = C_7'(L)\Delta x_{wp,t-1} + C_8'(L)F\left(f_{ir,t}, f_{sm,t}, f_{sq,t}, f_{sy,t}\right) \quad (2.12a)$$

$$\Delta x_{wp,t} = C_7''(L)\Delta x_{wp,t-1} + C_8''(L)F(f_{mm,t}, f_{mq,t}, f_{my,t}) \quad (2.12b)$$

Here,$C_7'(L), C_8'(L), C_7''(L)$, $C_8''(L)$ are lag polynomial matrices. Equations (2.12a) and (2.12b), respectively, forecasts the world export price index with separated and mixed FCIs.
Althugh there is rarely any study developing a theoretical model that presents the direct relation between the import price and financial conditions, some indirect transmission channel from FCIs to the world export price index is identified in the literature. Huybens and Smith (1999) developed a two-period, inter-temporal model to explain the strongly negative correlation between inflation and domestic financial conditions. In the context of this research, inflation of an exporting country will be reflected in its export price. Chor and Manova (2012) empirically found a structural shift of import volume during the 2008 crisis, owing to the credit availability shift of an exporting country. In a word, international financial conditions can ex-

[32] This setting takes the marginal predictive power of FCIs into account. As will be shown, FCIs' forecasting model, if it outperforms the benchmark model, it only improves at a small margin. If the p-value of the MDM statistics of FCIs vs. benchmark model is larger than 0.05 and

plain the world export price index in terms of its weight and export price index, that is, λ_i *and* p_i in Equation (2.8). In order to see whether the world export price index predicted by additional FCIs can enhance the forecasting performance of separated FCIs and mixed FCIs, a second two-way encompassing test is carried out.

Scenario B Given that the world export price index is predicted by Equation (2.12a), predictive tests of separated FCIs' forecasting model vs. benchmark model is carried out. And given that world export price index is predicted by Equation (2.12b), predictive tests of mixed FCIs' forecasting model vs. benchmark model is carried out.

In addition, since it is possible that FCIs have positive predictive power in forecasting the world export price index but negative predictive power in forecasting the import price index, it is necessary to control for the general FCIs' forecasting model. The predictive power of FCIs in forecasting the world export price is tested under another two scenarios.

Scenario C Separated FCIs' forecasting model with the world export price index predicted by Equation (2.11) are compared with the same separated FCIs' forecasting model but with the the world export price index predicted by Equation (2.12a).

Scenario D Mixed FCIs' forecasting model with the world export price index predicted by Equation (2.5) are compared to the same mixed FCIs' forecasting model but with the world export price index forecasted by Equation (2.12b).

2.3 Empirical Results

With respect to the six target economies, this section first discusses the in-sample modelling; then discusses the out-of-sample forecasting performance under the four scenarios mentioned above.

2.3.1 In-sample modelling results

Appendix 2B lists the in-sample modelling results and reports three types of statistics—standard error, partial R-squared and Hansen test statistics[34]--of each coefficient. The main findings are:

- Both separated FCIs and mixed FCIs are in-sample significant; particularly, long-run separated FCIs are significant in-sample for all six target economies, except Malaysia.

[34]Hansen statistics are used to evaluate model stability. If rejected at the 5% significance level, the model is likely to be unstable and, therefore, potentially fails to predict the target; see (Hansen 1992).

Since the long-run separated FCIs are aggregated from long-run indicators exclusively, this finding supports the postulation by QH that long-run indicators should contain more predictive information.

- The short-run world export price index is not significantly affected by FCIs when comparing benchmark forecasting models with FCIs' forecasting model. It seems against a postulation made in this chapter (Subsection 2.2.2) that since the information content of the world export price index overlaps that of international FCIs, a substitutive effect is expected when FCIs enter into the forecasting model. The failed postulation can be explained by partial R-squared statistics. Both separated and mixed FCIs only contribute marginal predictive power compared to macro predictors in the short run and, therefore, the substitutive effect between FCIs and the world export price is not obvious.

In addition to the findings that are common to all six of the target economies, macro predictors and FCIs have their unique form regarding each individual target economy.

Singapore

- As to the benchmark model, it is the short-run domestic exchange rate that overwhelmingly dominates other macro predictors. This finding is in sharp contrast to Sahminan (2005) who found that the short-run domestic exchange rate is insignificant. The short-run world export price index is second to the short-run domestic exchange rate.
- Various forms of FCIs are likely to be significant in-sample when they are additionally included in both the separated and the mixed FCIs' forecasting model. The monthly and quarterly short-run FCIs and long-run FCIs are all in-sample significant in the separated FCIs' forecasting model; monthly mixed FCIs, $f_{m,t}^{1}$ and annual mixed FCIs, $f_{y,t}^{3}$, are both in-sample significant.

Korea

- As to the benchmark model, the short-run world export price plays a significant role in the benchmark model. Domestic export price reaches a merely equally important position, signalling significant pricing-to-market effects in short run (Warmedinger 2004). Only the world export price enters into the EC term; a model specification corroborates the EC term specification in Higgins and Klitgaard (2000, 43).

- The same dynamic form of long-run FCIs, as in the case of Singapore, $\Delta f^{2}_{lr,t-5}$, is in-sample significant.

Taiwan

- The specification of the benchmark model is similar to that in the case of Korea. The world export price dominates in the benchmark model, while the domestic export price is second in dominance in the benchmark model.
- All dynamic forms of FCIs enter in the FCIs' forecasting model: monthly, quarterly, and annual short-run FCIs, as well as long-run FCIs are all in-sample significant in the separated FCIs' forecasting model; mixed monthly, quarterly, and annual FCIs are in-sample significant for the mixed FCIs' forecasting model.

Thailand

- As to the benchmark model, the first two lags of the dependent variable dominates macro predictors in the short run.
- The additional entry of FCIs enhances the feedback effect, that is, a coefficient of error-correction term rises from 0.01 to 0.02.

Indonesia

- As to the benchmark model, the domestic export price index is included in the long-run error correction term. The domestic exchange rate and export price index dominates the short-run volatility.
- It is notable that while own lags of the dependent variable are in-sample significant in the benchmark model, they are substituted by FCIs in both the separated and mixed FCIs' forecasting model. It signals that FCIs provide important leading information that is not modelled by macro predictors.

Malaysia

- As to the benchmark model, only lags of the dependent variable are in-sample significant. The drop-off of the domestic exchange rate is due to the fact that Malaysia fixed the exchange rate for a few years post ACC, as shown in Chapter 1.

2.3.2 Forecasting evaluation

The forecasting performance is statistically evaluated by an out-of-sample encompassing test; for MDM statistics, see Harveyet al. (1998). It is based on the commonly used Mean Squared Forecasting Error (MSFE), which is used in particular to measure the multi-horizon (from 1-step ahead to 18-step ahead) forecasting performance. The detailed empirical results are reported from Table 2.2 to Table 2.13 and a summary can be found in Table 2.14. In general, the separated FCIs' forecasting model outperforms both mixed FCIs and the benchmark forecasting model, with respect to Singapore, Korea, Taiwan, and Indonesia.

Singapore

- Under Scenarios A and B, the two-way MDM statistics and p-value show that the separated FCIs' forecasting model outperforms both the benchmark and mixed FCIs' forecasting model up to 9-months ahead forecasting, while the mixed FCIs' forecasting model is inferior to the benchmark model.

Under Scenarios C and D, modelling the world export price additionally by either the separated or mixed FCIs can indirectly improve the forecasting accuracy of final target, the import price index, in near future.

Korea

- Similar findings are found as in the Singapore case. Under Scenarios A and B, the separated FCIs' forecasting model outperforms both the benchmark and mixed FCIs' forecasting models across all forecasting horizons, while the mixed FCIs' forecasting model is inferior to the benchmark model.

Under Scenarios C and D, modelling the world export price additionally by either the separated or mixed FCIs can indirectly improve the forecasting accuracy of the final target, the import price index, in near future as well.

Taiwan

- Under Scenario A, the two-way MDM statistics and p-value show that the separated FCIs' forecasting model outperforms both the benchmark and mixed FCIs' forecasting model across all forecasting horizons.
- Under Scenario B, however, both the separated FCIs and mixed FCIs forecasting models tend to increase the predictive power, firstly up to 1 or 2 months ahead, and then

turns into noise throughout the second quarter ahead, finally regaining the predictive power up to 18-months ahead.

Under Scenarios C and D, modelling the world export price additionally, by either the separated or mixed FCIs, tends to contribute noise rather than signal throughout the first quarter ahead, while gradually regaining the predictive power from the second quarter forward.

Thailand

- FCIs basically fail to improve the forecasting under any scenario. Under Scenarios A and B, both separated and mixed FCIs contribute nothing but noise throughout all forecasting horizons, while separated FCIs still outperform mixed FCIs.

The same findings are obtained under Scenarios C and D: FCIs fail to contribute positive predictive power to model the world export price index.

Indonesia

- Under Scenarios A and B, the separated FCIs' forecasting model outperforms both the benchmark and mixed FCIs' forecasting models across all forecasting horizons, while the mixed FCIs' forecasting model can only improve the forecasting of the import price index in the very near future, a quarter ahead, based on the benchmark model.

Under Scenarios C and D, modelling the world export price additionally by either separated or mixed FCIs can indirectly improve the forecasting accuracy of the final target, the import price index, throughout all forecasting horizons.

Malaysia

Identical to Thailand, the FCIs fail to improve the forecasting under all four Scenarios.

Even for two economies—Thailand and Malaysia—where both separated and mixed FCIs' forecasting model underperformed in comparison to the benchmark forecasting model, the separated FCIs' forecasting model is found to be superior against mixed FCIs' forecasting model. In fact, such superiority is quite a large margin. From Figure 2.4, in terms of both forecasting the import price index and world export price index, MSFE of the separated FCIs is only a quarter of that of the mixed FCIs in short-term forecasting in the case of Malaysia, while the gap between MSFE of separated FCIs and that of mixed FCIs tends to be gradually larger along with the increasing forecasting horizon in the case of Thailand. In a word, the six economies all support the superiority of separated FCIs against mixed FCIs in terms of predictive power. The reason why QH could not verify the postulation from their own study is due to the differences in experimental design: (1) QH only targeted one economy, China, and it was possibly by chance that they found the separated FCIs had equal predictive power as the mixed FCIs, while empirical findings of this chapter lower the randomness through multi-economy research; (2) QH relied on *ex post* FCIs, the time series pattern of which is distinctively different from that of *ex ante* FCIs, and therefore the *ex ante* research adopted by this thesis has different findings; (3) QH's *ex post* FCIs could not highlight the advantage of separated FCIs over mixed FCIs in an *ex ante* context. Specifically, in an *ex ante* context, out-of-sample FCIs are required to be forecasted. And because long-run FCIs have slow dynamics, they can be more efficiently forecasted by their own lags than short-run FCIs.

2.4 Conclusion

Several findings are worth highlighting through multi-economy empirical research. First, since this chapter allows trade-related macro predictors to model the import price index, FCIs have much less explanatory power than the macro predictors in-sample and only contribute marginal predictive power as compared to the macro predictors out-of-sample. This result is not found in other studies due to the difference in the experimental design. Studies such as Hatzius et al. (2010); Qin and He (2012); Debuque-Gonzales and Gochoco-Bautista (2013) only found that FCIs can improve the forecasting of the target by 20% on average. Such a large margin is due to the fact that they specify an AR model as a benchmark forecasting model, as argued in Section 2.1.

Secondly, the separated FCIs outperform the mixed FCIs across all six of the target economies. This finding supports QH's postulation that the mixed FCIs, aggregated from a mixed set of long-run and short-run indicators, may lose predictive power compared to the separated FCI.

Thirdly, the investigation on each target economy shows that FCIs can successfully improve the forecasting performance with respect to Singapore, Korea, Taiwan, and Indonesia, but fail for Thailand and Malaysia. Admittedly, this finding is inconsistent with the relatively less opened financial sectors—Thailand and Malaysia both strictly intervened in their foreign exchange markets (see in Chapter 1); there is another finding that put FCIs estimated by DFM into question—the specification of both separated and mixed DFM FCIs' forecasting models are counter-intuitive in two respects.

- It is FCIs of considerable long lag that improve the prediction rather than FCIs of short lag. Taking the separated FCIs forecasting model as an example, differenced long-run FCIs of 5-month lagged, that is, $\Delta f^2_{lr,t-5}$, are in-sample significant in the FCIs' forecasting model in both the case of Korea and Singapore. And FCIs of long lag are also found to be in-sample significant in the case of Thailand and Indonesia.[35] Although it is a reasonable assumption that external financial markets lead the domestic import price index, it defies common sense that they can lead for almost half of a year, or at least that long lagged FCIs should not be frequently found in forecasting models across the six target economies.

- Across the six target economies, long-run FCIs in differenced form are more frequently found in-sample significant than long-run FCIs in level form. In fact, level long-run FCIs are only in-sample significant when forecasting the import price index of Taiwan. According to Aramonte et al. (2013), FCIs should enter the regressions at level because financial conditions should have real effects when they move out of a normal range. In addition, in an economic sense, the level long-run FCIs directly reflect financial market misalignment, that is, key leading information for forecasting purposes, and they should survive more frequently in FCIs forecasting models than differenced long-run FCIs. Additionally, because of their low frequency feature, level long-run FCIs should help predict the import price index more effectively than others, namely, the differenced long-run FCIs and short-run FCIs.

These two counter-intuitive specifications of FCIs' forecasting models, combined with their forecasting failure for Thailand and Malaysia, motivate further experimentation on FCIs that are estimated by an alternative method, to see whether they can be included in the forecasting model with the two counter-intuitive specifications and/or have superior predictive power against the benchmark model, with respect to all six target economies.

[35] Differenced long-run FCIs of 4-month lagged, that is, $\Delta f^{1}_{lr,t-4}$, is in-sample significant in the FCIs forecasting model in the case of Thailand; and differenced monthly short-run FCIs of 5-month lagged, that is, $f^{1}_{sm,t-5}$ is in-sample significant in the forecasting model in the case of Indonesia

Appendix 2A. Brief lists of QH's financial variables and indicators

1. A brief list of QH's financial variables for indicators

Name	Description	Database
R_BRate_DE	German: 10 Y government bond	CEIC
R_BRate_EU	European Central Bank: 10 Y government bond	CEIC
R_BRate_JP	Bank of Japan: 10 Y government bond	CEIC
R_BRate_UK	UK: Office of National Statistics: 10 Y government bond	CEIC
R_BRate_US	US: Federal Reserve Board: 20Y government bond	CEIC
R_ComP	World Bank LMICs	CEIC
R_CPI_JP	Japan: Consumer Price Index	DataStream
R_CPI_UK	UK: Consumer Price Index	DataStream
R_CPI_US	US: Consumer Price Index	DataStream
R_Deposit_UK	UK: Bank of England: Volume: Deposit	CEIC
R_Deposit_US	US: Federal Reserve Board: Volume: Deposit	CEIC
R_EMF_US	Index: Standard & Poors: Financial: Standard & Poor's	CEIC
R_EP_JP	JP: Index: Share Price	CEIC
R_EP_UK	UK: Index: Share Price	CEIC
R_EP_US	US: Index: Share Price	CEIC
R_Equityyield_UK	UK: Dividend Yield: FTSE	CEIC
R_Equityyield_US	Reuter: S&P500 Dividend Yield	DataStream
R_ER_EU	EUR/USD	CEIC
R_ER_JP	JPY/USD	CEIC
R_ER_UK	GBP/USD	CEIC
R_ERF_EU	European Central Bank: Forex Reference Rate	CEIC
R_ERF_JP	Japan: Forward Exchange Rate: 3 M	CEIC
R_ERF_UK	UK: Forward Exchange Rate: 3 M	CEIC
R_FI_EU	EU: Reuter: Futures Index	DataStream
R_FI_JP	JP: Reuter: Futures Index	DataStream
R_FI_US	US: Reuter: Futures Index	DataStream
R_HP1_JP	TSE Home Price Index: Tokyo	CEIC
R_HP2_JP	TSE Home Price Index: Kanagawa	CEIC
R_HP3_JP	TSE Home Price Index: Chiba	CEIC
R_HP4_JP	TSE Home Price Index: Saitama	CEIC
R_HP_JP	R_HP1_JP+R_HP2_JP+R_HP3_JP+R_HP4_JP	CEIC
R_HP_UK	UK: House Price	CEIC
R_HP_US	US: House Price	CEIC
R_BarclaysGB	Barclays Global bond index	DataStream
R_LOAN_UK	UK: Bank of England: Volume: Loan	CEIC
R_LOAN_US	US: Bank of England: Volume: Loan	CEIC
R_LIBOR_JP	JP: Overnight interest rate	CEIC

R_LIBOR_EU	EU: Overnight interest rate	CEIC
R_LIBOR_UK	UK: Overnight interest rate	CEIC
R_M1_JP	JP: Money Supply: M1	CEIC
R_M1_UK	UK: Money Supply: M1	CEIC
R_M1_US	US: Money Supply: M1	CEIC
R_MRATE_EU	EU: European Central Bank: 3 M interbank rate	CEIC
R_MRATE_JP	JP: Bank of Japan: 3 M Uncollaterized Call rate	CEIC
R_MRATE_UK	UK: Office of National Statistics: 3M interbank rate	CEIC
R_Mrate_US	US: US Dollar 3 M BBA libor	CEIC
R_OIS_EU	EU: Overnight Interest Swap	DataStream
R_OIS_UK	UK: Overnight Interest Swap	DataStream
R_OIS_US	US: Overnight Interest Swap	DataStream
R_ORF_EU	EU: Open interest: Total Futures	CEIC
R_ORFF_US	US: Open Interest: Financial Futures	CEIC
R_ORO_JP	JP: Open interes: Nikkei 225 Options	CEIC
R_S&P_US	US: S&P 500 Index	CEIC
R_S&PF_US	US: S&P Financial Index	CEIC
R_SPT_US	US: S&P Gobal 100 Index	CEIC
R_SPTF_US	US: S&P S&P Global 100 Financial Index	CEIC
R_Trate_DE	German: 1 Y Debt Sec Yield	CEIC
R_Trate_JP	JP: T bill rate	CEIC
R_Trate_UK	UK: T bill rate	CEIC
R_Trate_US	US: T bill rate	CEIC
R_TSE_JP	JP: TSE 1st Section Composite	CEIC
R_TSEF_JP	JP: TSE 1st Section Bank	CEIC

2. A brief list of QH's long-run financial variables

Market misalignment types (abbr.)	Indicator Name	Calculation[36]	Variable name and Data Source[37]			
Bond market vs. Equity market (BE)	BE_R_UK	1 – 2	R_BRate_UK		R_ EquityYield _UK	
	BE_R_US	1 – 2	R_BRate_US		R_ EquityYield _US	
Money market vs. Forex market (CIP)	CIP_EU	(1 – 2) - (ln(3) – ln(4))	R_MRate_JP	R_MRate_US	R_ERF_JP	R_ER_JP
	CIP_JP	(1 – 2) - (ln(3) – ln(4))	R_MRate_UK	R_MRate_US	R_ERF_UK	R_ER_UK
	CIP_UK	(1 – 2) - (ln(3) – ln(4))	R_MRate_UK	R_MRate_US	R_ERF_UK	R_ER_UK
Equity market vs. Commodity market (ECPI)	ECPI_R_UK	1 / 2	R_EP_UK		R_CPI_UK	
	ECPI_R_US	1 / 2	R_EP_US		R_CPI_US	
Bond market: Yield structure (GOV)	Gov_SP_DE	1 – 2	R_Brate_DE		R_Trate_DE	
	Gov_SP_JP	1 – 2	R_Brate_JP		R_Trate_JP	
	Gov_SP_UK	1 – 2	R_Brate_UK		R_Trate_UK	
	Gov_SP_US	1 – 2	R_Brate_US		R_Brate_US	
Money market: Yield structure (Mrate)	MRate_SP_JP	1 – 2	R_libor_JP		R_Mrate_JP	
	MRate_SP_UK	1 – 2	R_libor_UK		R_Mrate_UK	
Equity market	S&P_R_US	1 / 2	R_S&PF_US		R_S&P_US	
TED spread	TED_SP_UK	1 – 2	R_Mrate_UK		R_Trate_UK	
	TED_SP_US	1 – 2	R_Mrate_US		R_Trate_US	
Forex market	ERFER_SP_UK	1 – 2	R_ERF_UK		R_ER_UK	
Money market vs. Commodity market (RRate)	RRate_3m_UK	1 / g(2)[38]	R_Mrate_JP		R_CPI_UK	
	RRate_3m_US	1 / g(2)	R_Mrate_JP		R_CPI_UK	
Banking sector	LD_R_US	1 / 2	R_Loan_US		R_Deposit_US	

[36] Calculation of the stationary indicator from financial variables listed in its right column. The number in each cell denotes the column number. For example, the calculation of BE_R_UK is R_Brate_UK-R_Brate_UK, namely the 1st column minus the 2nd column to its right.

[37] Since for the DH list, the data source in detail and this research basically use the same financial variables,the data source in detail is not listed. For a detailed data source, please refer to QH's Appendix (Qin and He 2012, 28–29).

[38] 'g( )' denotes growth rate transformation

3. A brief list of QH's short-run financial variables39

Indicator name	Variable name
Brate_EU	Δ(R_BRate_EU)
Brate_FR	Δ(R_BRate_FR)
BRate_JP	Δ(R_BRate_JP)
BRate_UK	Δ(R_BRate_UK)
BRate_US	Δ(R_BRate_US)
MRATE_EU	Δ(R_MRate_EU)
MRATE_JP	Δ(R_MRate_JP)
MRATE_UK	Δ(R_MRate_UK)
Mrate_US	Δ(R_MRate_US)
ER_JP	g(R_ER_JP)
ER_UK	g(R_ER_UK)
Comp	g(R_Comp)
EMF_US	g(R_EMF_US)
EP_JP	g(R_EP_JP)
EP_UK	g(R_EP_UK)
EP_US	g(R_EP_US)
BarclayGB	g(R_BarclayGB)
LOAN_JP	Δ(R_Loan_JP-g(R_CPI_JP))
LOAN_UK	Δ(R_Loan_UK-g(R_CPI_UK))
LOAN_US	Δ(R_Loan_US-g(R_CPI_US))
M1_JP	Δ(R_M1_JP-g(R_CPI_JP))
M1_UK	Δ(R_M1_UK-g(R_CPI_UK))
M1_US	Δ(R_M1_US-g(R_CPI_US))
ORFF_US	g(R_ORF_US)
ORO_JP	g(R_ORO_JP)
ORF_JP	g(R_ORF_JP)
SPT_US	g(R_S&PT_US)

[39] This is a summary of short-run indicators. For a full list, please refer to Appendix 2 of Qin and He (2012).

Appendix 2B Parsimonious specification of the general forecasting models[40]

1. Singapore

$$\Delta SG_t = 0.15\Delta_2 SG_{wp,t} - 0.79\Delta SG_{er,t} + 0.0019 f^1_{sm,t-5} + 0.0027\Delta f^1_{sq,t-2} + 0.0045\Delta f^2_{lr,t-5} - 0.028\left(SG - SG_{wp}\right)_{t-1} + \varepsilon_t \quad (2.4a)$$

(0.028)	(0.045)	(0.00174)	(0.00174)	(0.0023)	(0.013)	(0.0083)
(0.12)	*(0.61)*	*(0.033)*	*(0.065)*	*(0.020)*	*(0.025)*	
(0.98)*	*(0.14)*	*(0.124)*	*(0.044)*	*(0.10)*	*(0.093)*	*(1.98*)*

$$\Delta SG_t = 0.14\Delta SG_{wp,t} + 0.12\Delta SG_{wp,t-1} - 0.83\Delta SG_{er,t} + 0.00159 f^1_{m,t-2} + 0.00154\Delta f^3_{y,t} - 0.038\left(SG - SG_{wp}\right)_{t-1} + \varepsilon_t \quad (2.4b)$$

(0.039)	(0.040)	(0.049)	(0.00118)	(0.00121)	(0.014)	(0.0090)
(0.064)	*(0.046)*	*(0.58)*	*(0.049)*	*(0.032)*	*(0.036)*	
(1.46)*	*(0.071)*	*(0.35)*	*(0.058)*	*(0.22)*	*(0.20)*	*(2.48*)*

$$\Delta SG_t = 0.10\Delta_2 SG_{wp,t} + 0.068\Delta_4 SG_{wp,t} - 0.78\Delta SG_{er,t} - 0.026\left(SG - SG_{wp}\right)_{t-1} + \varepsilon_t \quad (2.4c)$$

(0.038)	(0.029)	(0.047)	(0.013)	(0.0085)
(0.036)	(0.026)	(0.58)	(0.021)	
(0.823)*	*(0.41)*	*(0.123)*	*(0.125)*	*(1.40)*

[40] Variables in the equations are logarithmically transformed, while the prefix L is omitted for brief expression. Statistics in the upper parentheses are standard deviations; those in the middle parentheses are partial R-squared; those in the lower parentheses are Hansen test statistics, while the p-values that fall below 5% are marked by*. Values in the upper case middle case and lower case of residual, however, respectively, denote equation standard error (recorded as $sigma = \sqrt{\frac{Residual\ sum\ of\ squares}{no.of\ obs - no.\ of\ para}}$), joint R-squared, and the joint Hansen test statistics.

2. Korea

$$\Delta KOR_t = 0.70\Delta KOR_{dp,t} + 0.45\Delta KOR_{wp,t} + 0.19\Delta KOR_{wp,t-1} - 0.047\Delta\Delta KOR_{er,t-3} + 0.0081\Delta f^{2}_{lr,t-5} + 0.002\Delta f^{1}_{sm,t-3} - 0.0156\left(KOR - KOR_{wp}\right)_{t-1} + \varepsilon_t$$

(0.067)	(0.053)	(0.053)	(0.020)	(0.0025)	(0.0016)	(0.0048)	(0.0098)	
(0.35)	(0.27)	(0.059)	(0.028)	(0.052)	(0.030)	(0.052)		(2.4a)
(0.71*)	(2.79*)	(0.187)	(0.039)	(0.1025)	(0.0721)	(0.27)	(3.76*)	

$$\Delta KOR_t = 0.76\Delta KOR_{dp,t} + 0.43\Delta KOR_{wp,t} + 0.17\Delta KOR_{wp,t-1} - 0.045\Delta\Delta KOR_{er,t-3} + 0.00174\, f^{1}_{q,t} + 0.006\Delta f^{2}_{y,t-5} - 0.018\left(KOR - KOR_{wp}\right)_{t-1} + \varepsilon_t$$

(0.067)	(0.053)	(0.053)	(0.020)	(0.0012)	(0.0023)	(0.0047)	(0.0097)	
(0.40)	(0.25)	(0.051)	(0.026)	(0.066)	(0.033)	(0.067)		(2.4b)
(0.519*)	(2.03*)	(0.11)	(0.029)	(0.1397)	(0.406)	(0.073)	(3.05*)	

$$\Delta KOR_t = 0.738\Delta KOR_{dp,t} + 0.45\Delta KOR_{wp,t} + 0.20\Delta KOR_{wp,t-1} - 0.048\Delta\Delta KOR_{er,t-3} - 0.01\left(KOR - KOR_{wp}\right)_{t-1} + \varepsilon_t$$

(0.069)	(0.055)	(0.0538)	(0.020)	(0.0047)	(0.0101)	(2.4c)
(0.37)	(0.26)	(0.067)	(0.028)	(0.027)		
(0.559*)	(2.69*)	(0.12)	(0.026)	(0.2056)	(3.41*)	

3. Taiwan

$$\Delta TW_t = 0.56\Delta TW_{dp,t} + 0.50\Delta TW_{wp,t} + 0.16\Delta TW_{wp,t-1} + 0.0058\Delta f^1_{sq,t-2} - 0.0036\Delta_3 f^1_{sm,t-2} + 0.0018 f^1_{sy,t} + 0.00151 f^1_{lr,t-4} - 0.032\left(TW - 2.23TW_{wp} + 1.21TW_{dp}\right)_{t-1} + \varepsilon_t \tag{2.4a}$$

(0.10)	(0.049)	(0.051)	(0.0017)	(0.001)	(0.00126)	(0.0012)	(0.0084)	(0.0076)
(0.13)	(0.35)	(0.046)	(0.059)	(0.043)	(0.048)	(0.032)	(0.068)	
(0.11)	(0.38)	(0.024)	(0.077)	(0.096)	(0.11)	(0.155)	(0.036)	(1.04)

$$\Delta TW_t = 0.49\Delta TW_{dp,t} + 0.51\Delta TW_{wp,t} + 0.24\Delta TW_{wp,t-1} - 0.015\Delta f^1_{m,t-2} + 0.020\Delta f^1_{q,t-2} - 0.0074\Delta\Delta f^2_{q,t} + 0.00156 f^3_{y,t} - 0.032\left(TW - 2.23TW_{wp} + 1.21TW_{dp}\right)_{t-1} + \varepsilon_t \tag{2.4b}$$

(0.10)	(0.047)	(0.048)	(0.005)	(0.005)	(0.002)	(0.0012)	(0.006)	(0.0073)
(0.11)	(0.37)	(0.11)	(0.048)	(0.088)	(0.059)	(0.045)	(0.13)	
(0.166)	(0.57*)	(0.073)	(0.135)	(0.12)	(0.12)	(0.078)	(0.12)	(1.57)

$$\Delta TW_t = 0.64\Delta TW_{dp,t} + 0.47\Delta TW_{wp,t} + 0.17\Delta TW_{wp,t-1} - 0.042\Delta_4 TW_{er,t} - 0.028\left(TW - 2.23TW_{wp} + 1.21TW_{dp}\right)_{t-1} + \varepsilon_t \tag{2.4c}$$

(0.10)	(0.052)	(0.052)	(0.018)	(0.0063)	(0.0078)
(0.17)	(0.30)	(0.050)	(0.026)	(0.086)	
(0.028)	(0.189)	(0.0588)	(0.043)	(0.136)	(0.77)

4. Thailand

$$\Delta TH_t = -0.41\Delta TH_{t-1} + 0.16\Delta TH_{t-2} + 0.30\Delta TH_{dp,t} + 0.27\Delta TH_{wp,t} + 0.003f^1_{sq,t-1} - 0.007\Delta f^1_{sy,t-2} + 0.009\Delta f^1_{ir,t-4} - 0.02\left(TH - TH_{wp}\right)_{t-1} + \varepsilon_t \qquad (2.4a)$$

(0.064)	(0.064)	(0.10)	(0.0748)	(0.00175)	(0.002)	(0.0037)	(0.005)	(0.0145)
(0.18)	(0.031)	(0.044)	(0.064)	(0.059)	(0.039)	(0.030)	(0.063)	
(0.168)	(0.036)	(0.09)	(0.224)	(0.079)	(0.029)	(0.046)	(0.086)	(2.3687*)

$$\Delta TH_t = -0.43\Delta TH_{t-1} + 0.17\Delta TH_{t-2} + 0.28\Delta TH_{dp,t} + 0.27\Delta TH_{wp,t} - 0.025\Delta_2 f^1_{m,t-3} - 0.004f^1_{q,t-1} + 0.023\Delta_2 f^1_{q,t-3} - 0.009\Delta f^2_{q,t} + 0.004f^1_{y,t} - 0.02\left(TH - TH_{wp}\right)_{t-1} + \varepsilon_t \qquad (2.4b)$$

(0.062)	(0.063)	(0.10)	(0.0724)	(0.0056)	(0.0017)	(0.0057)	(0.0036)	(0.0014)	(0.007)	(0.014)
(0.20)	(0.035)	(0.038)	(0.067)	(0.090)	(0.027)	(0.076)	(0.033)	(0.045)	(0.029)	
(0.16)	(0.026)	(0.056)	(0.017)	(0.063)	(0.175)	(0.059)	(0.661*)	(0.174)	(0.049)	(2.95*)

$$\Delta TH_t = -0.34\Delta TH_{t-1} + 0.215\Delta TH_{t-2} + 0.325\Delta TH_{dp,t} + 0.3\Delta TH_{wp,t} - 0.01\left(TH - TH_{wp}\right)_{t-1} + \varepsilon_t \qquad (2.4c)$$

(0.063)	(0.064)	(0.103)	(0.076)	(0.005)	(0.015)
(0.13)	(0.053)	(0.047)	(0.073)	(0.02)	
(0.13)	(0.033)	(0.098)	(0.26)	(0.14)	(2.27*)

5. Indonesia

$$
\begin{array}{llllllllll}
\Delta ID_t = & 0.41\Delta ID_{dp,t} & -0.59\Delta ID_{er,t} & +0.044\Delta_3 ID_{er,t} & -0.0017 f^1_{sq,t-4} & +0.0052\Delta f^1_{sq,t-5} & -0.0070\Delta f^2_{sy,t-4} & -0.0092\Delta_2 f^3_{ir,t-1} & -0.044\left(ID-0.175ID_{wp}-0.875ID_{dp}\right)_{t-1} & +\varepsilon_t \\
 & (0.036) & (0.026) & (0.0086) & (0.00179) & (0.0016) & (0.0033) & (0.0026) & (0.0086) & (0.013) \\
 & (0.54) & (0.82) & (0.16) & (0.039) & (0.081) & (0.037) & (0.096) & (0.18) & \\
 & (0.21) & (0.089) & (0.128) & (0.054) & (0.485) & (0.197) & (0.22) & (0.13) & (2.50^{*})
\end{array} \qquad (2.4a)
$$

$$
\begin{array}{lllllllll}
\Delta ID_t = & 0.39\Delta ID_{dp,t} & -0.62\Delta ID_{er,t} & +0.053\Delta_3 ID_{er,t} & -0.146\Delta_5 ID_{wp,t} & -0.0022 f^3_{y,t-2} & -0.026\left(ID-0.175ID_{wp}-0.875ID_{dp}\right)_{t-1} & +\varepsilon_t \\
 & (0.037) & (0.027) & (0.0098) & (0.049) & (0.00154) & (0.0092) & (0.013) \\
 & (0.48) & (0.81) & (0.20) & (0.070) & (0.13) & (0.063) & \\
 & (0.12) & (0.0104) & (0.206) & (0.177) & (0.090) & (0.164) & (1.55)
\end{array} \qquad (2.4b)
$$

$$
\begin{array}{lllllllll}
\Delta ID_t = & 0.42\Delta ID_{dp,t} & -0.60\Delta ID_{er,t} & -0.14\Delta\Delta ID_{er,t-3} & -0.196\Delta\Delta ID_{t-3} & -0.064\Delta\Delta ID_{t-4} & -0.039\left(ID-0.175ID_{wp}-0.875ID_{dp}\right)_{t-1} & +\varepsilon_t \\
 & (0.031) & (0.025) & (0.034) & (0.042) & (0.016) & (0.0079) & (0.012) \\
 & (0.61) & (0.84) & (0.13) & (0.16) & (0.13) & (0.18) & \\
 & (0.32) & (0.12) & (0.083) & (0.154) & (0.095) & (0.25) & (1.88)
\end{array} \qquad (2.4c)
$$

6. Malaysia

$$\Delta MA_t = -0.38\Delta MA_{t-1} - 0.24\Delta MA_{t-2} - 0.0057 f^1_{sm,t} - 0.0016 f^2_{sy,t-4} + 0.0177\Delta f^2_{sy,t-4} - 0.23\left(MA - MA_{wp}\right)_{t-1} + \varepsilon_t \qquad (2.4a)$$

(0.082)	(0.078)	(0.0056)	(0.00170)	(0.0057)	(0.058)	(0.020)
(0.17)	(0.08)	(0.066)	(0.049)	(0.086)	(0.13)	(0.396)
(0.18)	(0.25)	(0.51*)	(0.053)	(0.068)	(0.17)	(2.18*)

$$\Delta MA_t = -0.53\Delta MA_{wp,t-1} - 0.04 f^1_{m,t} + 0.036 f^1_{q,t} - 0.002 f^2_{q,t-4} - 0.009\Delta f^3_{y,t-1} - 0.003 f^3_{y,t-4} - 0.698\left(MA - MA_{wp}\right)_{t-1} + \varepsilon_t \qquad (2.4b)$$

(0.219)	(0.012)	(0.011)	(0.001)	(0.004)	(0.0012)	(0.085)	(0.0216)
(0.053)	(0.10)	(0.089)	(0.038)	(0.047)	(0.049)	(0.39)	(0.40)
(0.099)	(0.065)	(0.076)	(0.047)	(0.21)	(0.029)	(0.29)	(2.37*)

$$\Delta MA_t = -0.43\Delta MA_{t-1} - 0.22\Delta MA_{t-2} - 0.129\left(MA - MA_{wp}\right)_{t-1} + \varepsilon_t \qquad (2.4c)$$

(0.086)	(0.082)	(0.054)	(0.021)
(0.19)	(0.06)	(0.05)	
(0.14)	(0.16)	(0.05)	(1.79*)

Table 2.1 Determined number of factors and lag length in Equations (2.1) and (2.2)

	f_{lr}	f_{sm}	f_{sq}	f_{sy}	f_{mm}	f_{mq}	f_{my}
Number of factors	3	1	1	2	2	2	3
Lag length	1	1	2	2	1	1	2

Table 2.2 SG: Out-of-sample encompassing tests under the four scenarios[41]

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
Scenario A	(2.4a) vs	1.189	0.126	-0.988	-1.392	-1.579	-1.442	-1.283	-0.978	-0.25	0.919	2.277	3.481	4.105	4.514	4.732	4.947	4.802	4.342
(2.5)	(2.4c)	(0.12)	(0.45)	(0.836)	(0.916)	(0.94)	(0.923)	(0.898)	(0.834)	(0.598)	(0.181)	(0.013**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**
	(2.4c) vs	-0.037	0.93	1.945	1.971	1.984	1.762	1.601	1.352	0.73	-0.258	-1.55	-2.749	-3.442	-4.01	-4.407	-4.872	-4.819	-4.294
	(2.4a)	(0.515)	(0.178)	(0.028**	(0.027**	(0.026**	(0.042**	(0.057*)	(0.091*)	(0.234)	(0.601)	(0.936)	(0.996)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)
	(2.4b) vs	1.535	1.506	1.044	0.391	0.134	0.069	0.102	0.277	0.53	0.932	1.423	1.813	2.019	2.105	2.158	2.211	2.273	2.373
	(2.4c)	(0.065*)	(0.069*)	(0.072*)	(0.076*)	(0.08*)	(0.083*)	(0.087*)	(0.091*)	(0.094*)	(0.098*)	(0.102)	(0.105)	(0.109)	(0.113)	(0.116)	(0.12)	(0.124)	(0.127)
	(2.4c) vs	-0.638	-0.652	-0.229	0.289	0.504	0.611	0.66	0.568	0.406	0.113	-0.275	-0.635	-0.873	-1.029	-1.167	-1.299	-1.451	-1.641
	(2.4b)	(0.737)	(0.742)	(0.59)	(0.387)	(0.308)	(0.272)	(0.256)	(0.286)	(0.343)	(0.455)	(0.608)	(0.736)	(0.807)	(0.846)	(0.876)	(0.9)	(0.923)	(0.946)
	(2.4a) vs	0.001	-1.126	-1.548	-1.344	-1.653	-1.588	-1.668	-1.88	-2.067	-2.223	-2.236	-2.358	-2.473	-2.51	-2.525	-2.414	-2.421	-2.555
	(2.4b)	(0.5)	(0.868)	(0.937)	(0.908)	(0.948)	(0.941)	(0.95)	(0.967)	(0.978)	(0.985)	(0.985)	(0.989)	(0.992)	(0.992)	(0.993)	(0.99)	(0.99)	(0.993)
	(2.4b) vs	1.058	2.038	2.192	1.968	2.273	2.191	2.263	2.476	2.678	2.887	2.938	3.116	3.241	3.21	3.202	3.05	3.014	3.078
	(2.4a)	(0.147)	(0.023**	(0.016**	(0.027**	(0.013**	(0.016**	(0.014**	(0.008**	(0.005**	(0.003**	(0.002**	(0.001**	(0.001**	(0.001**	(0.001**	(0.002**	(0.002**	(0.002**
Scenario B	(2.4a) vs	1.121	0.136	-0.958	-1.298	-1.43	-1.334	-1.172	-0.894	-0.164	0.938	2.142	3.178	3.68	4.086	4.365	4.725	4.687	4.239
(2.6a)&(2.	(2.4c)	(0.133)	(0.446)	(0.829)	(0.9)	(0.921)	(0.906)	(0.877)	(0.812)	(0.565)	(0.176)	(0.018**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**
6b)	(2.4c) vs	0.07	0.959	1.937	1.9	1.855	1.663	1.498	1.28	0.634	-0.314	-1.475	-2.475	-2.977	-3.439	-3.803	-4.295	-4.339	-3.913
	(2.4a)	(0.472)	(0.171)	(0.029**	(0.031**	(0.034**	(0.051*)	(0.07*)	(0.103)	(0.265)	(0.623)	(0.927)	(0.992)	(0.998)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)
	(2.4b) vs	1.664	1.669	1.232	0.579	0.161	-0.15	-0.301	-0.308	-0.154	0.172	0.686	1.2	1.593	1.854	2.062	2.269	2.448	2.61
	(2.4c)	(0.051*)	(0.05*)	(0.111)	(0.282)	(0.436)	(0.559)	(0.618)	(0.621)	(0.561)	(0.432)	(0.248)	(0.118)	(0.059*)	(0.035**	(0.022**	(0.014**	(0.009**	(0.006**
	(2.4c) vs	-0.842	-0.901	-0.539	-0.053	0.287	0.578	0.762	0.816	0.723	0.478	0.061	-0.399	-0.792	-1.074	-1.304	-1.532	-1.759	-1.989
	(2.4b)	(0.798)	(0.814)	(0.704)	(0.521)	(0.388)	(0.283)	(0.225)	(0.209)	(0.236)	(0.317)	(0.476)	(0.654)	(0.784)	(0.856)	(0.901)	(0.934)	(0.957)	(0.974)
	(2.4a) vs	0.429	-1.083	-1.972	-1.977	-2.26	-2.417	-2.622	-2.8	-2.93	-3.208	-3.463	-3.73	-3.874	-3.865	-3.795	-3.634	-3.44	-3.281
	(2.4b)	(0.335)	(0.858)	(0.973)	(0.974)	(0.986)	(0.991)	(0.994)	(0.996)	(0.998)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)	(0.999)
	(2.4b) vs	0.929	2.421	3.035	2.973	3.186	3.34	3.499	3.67	3.795	4.064	4.285	4.508	4.59	4.499	4.319	4.083	3.848	3.652
	(2.4a)	(0.178)	(0.009**	(0.002**	(0.002**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**	(0.001**

[41] A p-value smaller than 0.05 implies at 5% significance level, that the latter outperforms the former in terms of forecasting power. For example, if the p-value of (2.4a) vs. (2.4c) is 0.04, it implies the benchmark forecasting model outperforms the separated FCIs forecasting model.

Scenario C (2.4a)	(2.6a) vs (2.5)	-0.269 (0.606)	-1.284 (0.898)	-1.203 (0.883)	-0.937 (0.824)	-0.708 (0.759)	-0.491 (0.687)	-0.331 (0.629)	0.038 (0.485)	0.424 (0.337)	0.738 (0.232)	0.98 (0.166)	1.21 (0.116)	1.353 (0.091*)	1.508 (0.069*)	1.564 (0.062*)	1.595 (0.059*)	1.672 (0.051*)	1.745 (0.044**
	(2.5) vs (2.6a)	0.749 (0.228)	1.892 (0.032**	1.829 (0.036**	1.59 (0.059*)	1.399 (0.084*)	1.203 (0.117)	1.089 (0.14)	0.757 (0.226)	0.407 (0.343)	0.159 (0.437)	-0.006 (0.503)	-0.226 (0.589)	-0.407 (0.657)	-0.597 (0.723)	-0.721 (0.763)	-0.831 (0.795)	-0.977 (0.833)	-1.144 (0.871)
Scenario D (2.4b)	(2.6b) vs (2.5)	-0.627 (0.734)	-0.736 (0.768)	0.112 (0.456)	1.013 (0.158)	1.414 (0.081*)	2.011 (0.024**	2.492 (0.008**	2.891 (0.003**	3.143 (0.001**	3.351 (0.001**	3.466 (0.001**	3.52 (0.001**	3.469 (0.001**	3.377 (0.001**	3.236 (0.001**	3.047 (0.002**	2.872 (0.003**	2.745 (0.004**
	(2.5) vs (2.6b)	0.91 (0.183)	1.067 (0.145)	0.382 (0.352)	-0.366 (0.642)	-0.704 (0.758)	-1.252 (0.892)	-1.692 (0.952)	-2.071 (0.979)	-2.316 (0.988)	-2.559 (0.993)	-2.732 (0.996)	-2.874 (0.997)	-2.906 (0.997)	-2.895 (0.997)	-2.833 (0.997)	-2.706 (0.995)	-2.576 (0.993)	-2.489 (0.992)

Table 2.3 SG: RMSFE under Scenarios A, B, and C

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
2.5	2.4a	0.021	0.039	0.053	0.066	0.075	0.083	0.087	0.090	0.091	0.091	0.091	0.092	0.095	0.099	0.103	0.108	0.113	0.118
	2.4b	0.021	0.040	0.054	0.067	0.077	0.085	0.089	0.091	0.092	0.091	0.090	0.089	0.090	0.093	0.094	0.097	0.100	0.104
	2.4c	0.021	0.039	0.054	0.067	0.077	0.085	0.089	0.091	0.092	0.090	0.089	0.087	0.088	0.090	0.091	0.093	0.095	0.098
2.6a	2.4a	0.021	0.038	0.052	0.065	0.075	0.082	0.087	0.089	0.091	0.091	0.092	0.094	0.097	0.102	0.107	0.112	0.119	0.125
	2.4c	0.021	0.038	0.054	0.067	0.078	0.086	0.091	0.094	0.096	0.096	0.095	0.096	0.098	0.101	0.105	0.108	0.112	0.117
2.6b	2.4b	0.021	0.039	0.054	0.067	0.078	0.086	0.091	0.094	0.095	0.096	0.096	0.097	0.099	0.103	0.107	0.111	0.116	0.121
	2.4c	0.021	0.039	0.053	0.066	0.076	0.084	0.088	0.091	0.091	0.091	0.090	0.089	0.090	0.093	0.096	0.099	0.102	0.106

Table 2.4 KOR: Out-of-sample encompassing tests under the four scenarios

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
Scenario A (2.5)	(2.4a) vs (2.4c)	0.889 (0.189)	-0.07 (0.528)	-1.742 (0.957)	-2.211 (0.985)	-2.211 (0.985)	-1.947 (0.972)	-1.941 (0.971)	-2.088 (0.979)	-2.13 (0.981)	-2.193 (0.984)	-2.213 (0.984)	-2.336 (0.988)	-2.51 (0.992)	-2.539 (0.993)	-2.712 (0.995)	-2.732 (0.996)	-2.856 (0.997)	-2.942 (0.997)
	(2.4c) vs (2.4a)	-0.061 (0.524)	0.827 (0.206)	2.107 (0.02**	2.343 (0.011**	2.283 (0.013**	1.996 (0.025**	1.98 (0.026**	2.118 (0.019**	2.155 (0.018**	2.214 (0.016**	2.234 (0.015**	2.354 (0.011**	2.522 (0.007**	2.547 (0.007**	2.711 (0.005**	2.728 (0.004**	2.848 (0.003**	2.93 (0.003**
	(2.4b) vs (2.4c)	2.17 (0.017**	2.192 (0.016**	1.763 (0.041**	1.423 (0.08*	1.169 (0.124)	1.389 (0.085*	1.656 (0.052*	1.918 (0.03**	2.136 (0.019**	2.353 (0.011**	2.609 (0.006**	2.798 (0.004**	2.907 (0.003**	2.94 (0.002**	2.95 (0.002**	2.931 (0.003**	2.884 (0.003**	2.81 (0.004**
	(2.4c) vs (2.4b)	-1.424 (0.92)	-1.472 (0.927)	-1.064 (0.854)	-0.81 (0.789)	-0.599 (0.724)	-0.833 (0.796)	-1.095 (0.861)	-1.344 (0.908)	-1.555 (0.937)	-1.768 (0.959)	-2.015 (0.975)	-2.198 (0.984)	-2.307 (0.987)	-2.355 (0.989)	-2.374 (0.989)	-2.357 (0.989)	-2.323 (0.988)	-2.274 (0.986)
	(2.4a) vs (2.4b)	-0.686 (0.752)	-2.037 (0.977)	-3.082 (0.998)	-3.776 (0.999)	-4.062 (0.999)	-3.993 (0.999)	-4.122 (0.999)	-4.23 (0.999)	-4.285 (0.999)	-4.348 (0.999)	-4.36 (0.999)	-4.348 (0.999)	-4.227 (0.999)	-4.135 (0.999)	-4.078 (0.999)	-3.962 (0.999)	-3.79 (0.999)	-3.594 (0.999)
	(2.4b) vs (2.4a)	1.671 (0.05*	2.765 (0.004**	3.501 (0.001**	3.992 (0.001**	4.23 (0.001**	4.205 (0.001**	4.332 (0.001**	4.416 (0.001**	4.457 (0.001**	4.508 (0.001**	4.518 (0.001**	4.504 (0.001**	4.386 (0.001**	4.295 (0.001**	4.244 (0.001**	4.142 (0.001**	3.972 (0.001**	3.772 (0.001**
Scenario B (2.6a)&(2.6 b)	(2.4a) vs (2.4c)	1.301 (0.099*	0.302 (0.382)	-1.762 (0.958)	-2.129 (0.981)	-2.184 (0.984)	-1.914 (0.97)	-1.905 (0.969)	-2.051 (0.977)	-2.091 (0.979)	-2.151 (0.982)	-2.158 (0.982)	-2.276 (0.987)	-2.447 (0.991)	-2.469 (0.991)	-2.626 (0.994)	-2.629 (0.994)	-2.717 (0.995)	-2.747 (0.996)
	(2.4c) vs (2.4a)	-0.623 (0.732)	0.366 (0.358)	2.197 (0.016**	2.298 (0.013**	2.266 (0.014**	1.968 (0.027**	1.949 (0.028**	2.085 (0.021**	2.12 (0.019**	2.177 (0.017**	2.185 (0.017**	2.302 (0.013**	2.469 (0.008**	2.489 (0.008**	2.642 (0.006**	2.644 (0.006**	2.734 (0.004**	2.771 (0.004**
	(2.4b) vs (2.4c)	2.53 (0.007**	2.708 (0.004**	2.314 (0.012**	1.968 (0.027**	1.683 (0.049**	2.008 (0.025**	2.329 (0.012**	2.625 (0.006**	2.857 (0.003**	3.078 (0.002**	3.35 (0.001**	3.545 (0.001**	3.65 (0.001**	3.667 (0.001**	3.668 (0.001**	3.643 (0.001**	3.573 (0.001**	3.451 (0.001**
	(2.4c) vs (2.4b)	-1.87 (0.967)	-2.1 (0.98)	-1.684 (0.951)	-1.401 (0.917)	-1.15 (0.873)	-1.503 (0.931)	-1.837 (0.964)	-2.132 (0.981)	-2.365 (0.989)	-2.592 (0.994)	-2.866 (0.997)	-3.062 (0.998)	-3.167 (0.999)	-3.195 (0.999)	-3.204 (0.999)	-3.177 (0.999)	-3.113 (0.998)	-3.008 (0.998)
	(2.4a) vs (2.4b)	0.656 (0.257)	0.053 (0.479)	-0.117 (0.546)	0.189 (0.426)	-0.136 (0.554)	-0.415 (0.66)	-0.829 (0.795)	-1.296 (0.9)	-1.572 (0.939)	-1.682 (0.951)	-1.949 (0.972)	-2.112 (0.98)	-2.252 (0.986)	-2.317 (0.988)	-2.323 (0.988)	-2.332 (0.988)	-2.311 (0.987)	-2.292 (0.987)
	(2.4b) vs (2.4a)	1.337 (0.093*	1.664 (0.051*	1.509 (0.068*	1.266 (0.105)	1.334 (0.094*	1.546 (0.064*	1.758 (0.042**	2.032 (0.023**	2.204 (0.016**	2.242 (0.015**	2.463 (0.009**	2.503 (0.008**	2.548 (0.007**	2.604 (0.006**	2.638 (0.006**	2.626 (0.006**	2.546 (0.007**	2.493 (0.008**

Scenario C (2.4a)	(2.6a) vs (2.5)	1.028 (0.474)	1.379 (0.426)	1.275 (0.34)	0.901 (0.221)	0.936 (0.331)	1.069 (0.422)	1.107 (0.484)	1.165 (0.512)	0.979 (0.454)	0.697 (0.357)	0.474 (0.274)	0.336 (0.235)	0.245 (0.2)	0.01 (0.147)	-0.25 (0.098*	-0.363 (0.084*	-0.433 (0.074*	-0.602 (0.055*
	(2.5) vs (2.6a)	1.028 (0.154)	1.379 (0.086*	1.275 (0.104)	0.901 (0.186)	0.936 (0.177)	1.069 (0.145)	1.107 (0.136)	1.165 (0.125)	0.979 (0.166)	0.697 (0.244)	0.474 (0.319)	0.336 (0.369)	0.245 (0.404)	0.01 (0.496)	-0.25 (0.598)	-0.363 (0.641)	-0.433 (0.667)	-0.602 (0.725)
Scenario D (2.4b)	(2.6b) vs (2.5)	-0.9 (0.814)	-0.467 (0.679)	-0.524 (0.699)	-0.628 (0.734)	-0.746 (0.771)	-0.766 (0.777)	-0.666 (0.746)	-0.49 (0.687)	-0.27 (0.606)	-0.008 (0.503)	0.282 (0.39)	0.594 (0.277)	0.881 (0.191)	1.105 (0.137)	1.325 (0.096*	1.514 (0.068*	1.718 (0.046**	1.896 (0.032**
	(2.5) vs (2.6b)	1.397 (0.084*	1.05 (0.149)	1.069 (0.145)	1.09 (0.14)	1.155 (0.126)	1.167 (0.124)	1.092 (0.14)	0.938 (0.176)	0.748 (0.229)	0.53 (0.299)	0.294 (0.385)	0.038 (0.485)	-0.198 (0.578)	-0.399 (0.654)	-0.587 (0.72)	-0.75 (0.771)	-0.929 (0.821)	-1.107 (0.863)

Table 2.5 KOR: RMSFE under Scenarios A, B, and C

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
2.5	2.4a	0.026	0.050	0.072	0.092	0.109	0.123	0.132	0.138	0.142	0.143	0.143	0.143	0.145	0.148	0.150	0.153	0.156	0.159
	2.4b	0.026	0.051	0.074	0.095	0.113	0.128	0.137	0.144	0.149	0.151	0.153	0.154	0.157	0.161	0.165	0.169	0.173	0.177
	2.4c	0.026	0.050	0.073	0.094	0.112	0.126	0.135	0.141	0.145	0.147	0.147	0.147	0.149	0.152	0.154	0.158	0.161	0.164
2.6a	2.4a	0.025	0.049	0.072	0.092	0.109	0.123	0.132	0.138	0.142	0.144	0.145	0.147	0.149	0.154	0.157	0.162	0.166	0.171
	2.4c	0.025	0.049	0.072	0.093	0.111	0.124	0.133	0.138	0.143	0.146	0.146	0.148	0.150	0.155	0.159	0.163	0.167	0.172
2.6b	2.4b	0.026	0.049	0.071	0.092	0.108	0.122	0.130	0.135	0.140	0.142	0.143	0.144	0.146	0.151	0.155	0.159	0.163	0.168
	2.4c	0.026	0.050	0.073	0.093	0.111	0.125	0.135	0.141	0.147	0.150	0.152	0.155	0.159	0.165	0.169	0.175	0.180	0.186

Table 2.6 TW: Out-of-sample encompassing tests under the four scenarios

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
Scenario A (2.5)	(2.4a) vs (2.4c)	-1.861	0.195	-0.399	1.188	-0.337	0.879	-0.384	0.256	-0.603	-0.095	-0.825	-0.456	-1.475	-0.979	-1.987	-1.42	-2.069	-1.608
		(0.966)	(0.423)	(0.654)	(0.12)	(0.631)	(0.191)	(0.649)	(0.399)	(0.725)	(0.538)	(0.793)	(0.675)	(0.927)	(0.834)	(0.974)	(0.919)	(0.978)	(0.943)
	(2.4c) vs (2.4a)	2.572	0.9	1.165	-0.208	1.025	0.037	1.008	0.497	1.173	0.781	1.369	1.042	1.894	1.395	2.26	1.621	2.26	1.68
		(0.006**	(0.186)	(0.124)	(0.582)	(0.155)	(0.485)	(0.159)	(0.311)	(0.123)	(0.219)	(0.088*	(0.151)	(0.032**	(0.085*	(0.014**	(0.056*	(0.014**	(0.05*
	(2.4b) vs (2.4c)	0.241	1.438	0.658	1.948	1.026	1.946	0.877	1.412	0.124	0.803	-0.572	0.089	-1.46	-0.639	-2.008	-1.399	-2.003	-1.685
		(0.405)	(0.078*	(0.256)	(0.028**	(0.154)	(0.028**	(0.192)	(0.082*	(0.451)	(0.213)	(0.715)	(0.465)	(0.925)	(0.737)	(0.975)	(0.916)	(0.975)	(0.951)
	(2.4c) vs (2.4b)	1.052	-0.018	0.436	-1.366	-0.052	-1.364	0.101	-0.788	0.791	-0.041	1.409	0.704	2.12	1.301	2.442	1.731	2.272	1.805
		(0.148)	(0.507)	(0.332)	(0.912)	(0.521)	(0.911)	(0.46)	(0.783)	(0.216)	(0.516)	(0.082*	(0.242)	(0.019**	(0.1*	(0.009**	(0.045**	(0.014**	(0.039**
	(2.4a) vs (2.4b)	-0.187	-0.517	-0.611	-1.165	-1.081	-1.675	-1.252	-1.753	-0.753	-1.387	0.169	-0.573	1.297	0.483	1.97	1.739	1.986	1.973
		(0.574)	(0.696)	(0.728)	(0.876)	(0.858)	(0.95)	(0.892)	(0.957)	(0.773)	(0.914)	(0.433)	(0.716)	(0.1*	(0.316)	(0.027**	(0.044**	(0.026**	(0.027**
	(2.4b) vs (2.4a)	1.433	1.579	1.438	1.667	1.547	1.934	1.633	1.959	1.136	1.602	0.196	0.85	-1.014	-0.101	-1.812	-1.506	-1.905	-1.898
		(0.078*	(0.06*	(0.078*	(0.05*	(0.064*	(0.029**	(0.054*	(0.028**	(0.131)	(0.057*	(0.422)	(0.2)	(0.842)	(0.54)	(0.962)	(0.931)	(0.969)	(0.968)
Scenario B (2.6a)&(2.6 b)	(2.4a) vs (2.4c)	-1.838	0.02	0.433	1.89	-0.209	0.561	-0.818	-0.42	-1.149	-0.759	-1.334	-1.075	-1.897	-1.446	-2.213	-1.675	-2.241	-1.723
		(0.965)	(0.492)	(0.333)	(0.032**	(0.583)	(0.289)	(0.792)	(0.662)	(0.872)	(0.774)	(0.906)	(0.856)	(0.968)	(0.923)	(0.984)	(0.95)	(0.985)	(0.954)
	(2.4c) vs (2.4a)	2.529	1.116	0.498	-0.941	0.905	0.306	1.34	1.089	1.591	1.345	1.75	1.554	2.215	1.763	2.434	1.814	2.394	1.768
		(0.007**	(0.134)	(0.31)	(0.825)	(0.184)	(0.38)	(0.093*	(0.14)	(0.059*	(0.092*	(0.043**	(0.063*	(0.016**	(0.042**	(0.009**	(0.038**	(0.01**	(0.042**
	(2.4b) vs (2.4c)	0.202	1.369	0.401	1.699	0.326	1.517	-0.067	0.87	-0.894	0.131	-1.494	-0.551	-2.172	-1.124	-2.454	-1.639	-2.258	-1.758
		(0.42)	(0.088*	(0.345)	(0.047**	(0.373)	(0.067*	(0.527)	(0.194)	(0.812)	(0.448)	(0.929)	(0.708)	(0.983)	(0.867)	(0.991)	(0.946)	(0.986)	(0.957)
	(2.4c) vs (2.4b)	1.057	0.017	0.617	-1.141	0.519	-0.975	0.893	-0.283	1.611	0.573	2.139	1.249	2.655	1.659	2.754	1.891	2.438	1.855
		(0.147)	(0.493)	(0.27)	(0.871)	(0.303)	(0.833)	(0.188)	(0.611)	(0.056*	(0.284)	(0.019**	(0.109)	(0.005**	(0.052*	(0.004**	(0.032**	(0.009**	(0.035**
	(2.4a) vs (2.4b)	0.06	0.496	1.118	1.458	1.218	1.322	1.172	1.266	1.268	1.724	1.523	1.993	1.454	2.204	1.541	2.351	1.445	2.087
		(0.476)	(0.311)	(0.134)	(0.075*	(0.114)	(0.096*	(0.123)	(0.105)	(0.105)	(0.045**	(0.067*	(0.026**	(0.076*	(0.016**	(0.065*	(0.011**	(0.078*	(0.021**
	(2.4b) vs (2.4a)	1.189	1.024	0.544	0.338	0.216	0.291	0.213	0.41	0.171	-0.003	-0.203	-0.307	-0.331	-0.747	-0.806	-1.411	-0.944	-1.567
		(0.119)	(0.155)	(0.294)	(0.368)	(0.415)	(0.386)	(0.416)	(0.342)	(0.432)	(0.501)	(0.58)	(0.62)	(0.629)	(0.771)	(0.788)	(0.918)	(0.825)	(0.938)

Scenario C (2.4a)	(2.6a) vs (2.5)	2.407 (0.01**	1.613 (0.056*	1.394 (0.084*	1.517 (0.067*	1.132 (0.131)	1.13 (0.132)	0.725 (0.236)	0.685 (0.248)	0.483 (0.316)	0.637 (0.263)	0.465 (0.322)	0.518 (0.303)	0.228 (0.41)	0.571 (0.285)	0.228 (0.41)	0.534 (0.298)	0.111 (0.456)	0.336 (0.369)
	(2.5) vs (2.6a)	-0.861 (0.804)	0.804 (0.212)	0.193 (0.424)	-0.059 (0.523)	0.128 (0.449)	0.41 (0.342)	0.644 (0.261)	1.079 (0.143)	1.021 (0.156)	1.205 (0.117)	1.005 (0.16)	1.415 (0.082*	1.129 (0.132)	1.198 (0.118)	0.825 (0.207)	0.82 (0.208)	0.735 (0.233)	0.579 (0.283)
Scenario D (2.4b)	(2.6b) vs (2.5)	1.301 (0.099*	0.622 (0.268)	0.114 (0.455)	-0.877 (0.808)	-0.619 (0.731)	-1.431 (0.921)	-1.284 (0.898)	-1.807 (0.962)	-1.374 (0.912)	-1.915 (0.97)	-1.348 (0.908)	-1.953 (0.972)	-1.2 (0.882)	-1.692 (0.952)	-0.901 (0.814)	-1.294 (0.899)	-0.42 (0.662)	-0.887 (0.81)
	(2.5) vs (2.6b)	-0.975 (0.833)	-0.097 (0.539)	0.531 (0.299)	1.734 (0.044**	1.507 (0.069*	2.371 (0.011**	2.154 (0.018**	2.682 (0.005**	2.224 (0.015**	2.776 (0.004**	2.207 (0.016**	2.784 (0.004**	2.045 (0.023**	2.471 (0.008**	1.663 (0.051*	1.989 (0.026**	1.048 (0.15)	1.456 (0.076*

Table 2.7 TW: RMSFE under Scenarios A, B, and C

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
2.5	2.4a	0.026	0.041	0.067	0.081	0.104	0.111	0.127	0.125	0.137	0.131	0.142	0.134	0.155	0.142	0.184	0.174	0.226	0.235
	2.4b	0.026	0.042	0.067	0.083	0.105	0.113	0.128	0.127	0.138	0.133	0.142	0.135	0.153	0.142	0.178	0.169	0.214	0.219
	2.4c	0.027	0.042	0.067	0.081	0.104	0.110	0.128	0.125	0.139	0.132	0.145	0.136	0.161	0.148	0.194	0.187	0.245	0.261
2.6a	2.4a	0.026	0.042	0.068	0.083	0.105	0.112	0.127	0.125	0.136	0.130	0.141	0.132	0.153	0.141	0.181	0.174	0.223	0.234
	2.4c	0.027	0.042	0.068	0.082	0.106	0.112	0.129	0.126	0.139	0.132	0.145	0.136	0.159	0.148	0.193	0.188	0.244	0.261
2.6b	2.4b	0.027	0.042	0.067	0.081	0.103	0.110	0.126	0.124	0.134	0.127	0.137	0.127	0.147	0.132	0.172	0.159	0.210	0.211
	2.4c	0.027	0.042	0.067	0.080	0.103	0.109	0.126	0.123	0.136	0.128	0.141	0.130	0.157	0.141	0.191	0.181	0.244	0.255

Table 2.8 TH: Out-of-sample encompassing tests under the four scenarios

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
Scenario A (2.5)	(2.4a) vs (2.4c)	2.641 (0.005**	3.148 (0.001**	3.457 (0.001**	3.64 (0.001**	3.699 (0.001**	3.806 (0.001**	4.132 (0.001**	4.253 (0.001**	4.585 (0.001**	4.84 (0.001**	5.159 (0.001**	5.282 (0.001**	5.148 (0.001**	5.063 (0.001**	4.839 (0.001**	4.625 (0.001**	4.404 (0.001**	4.19 (0.001**
	(2.4c) vs (2.4a)	-0.073 (0.529)	-0.745 (0.77)	-1.609 (0.944)	-2.269 (0.987)	-2.437 (0.991)	-2.72 (0.996)	-3.049 (0.998)	-3.209 (0.999)	-3.516 (0.999)	-3.797 (0.999)	-4.159 (0.999)	-4.384 (0.999)	-4.465 (0.999)	-4.528 (0.999)	-4.419 (0.999)	-4.263 (0.999)	-4.109 (0.999)	-3.943 (0.999)
	(2.4b) vs (2.4c)	4.341 (0.001**	4.929 (0.001**	5.283 (0.001**	5.362 (0.001**	5.439 (0.001**	5.195 (0.001**	5.111 (0.001**	4.968 (0.001**	4.842 (0.001**	4.653 (0.001**	4.444 (0.001**	4.183 (0.001**	3.958 (0.001**	3.732 (0.001**	3.511 (0.001**	3.306 (0.001**	3.087 (0.002**	2.877 (0.003**
	(2.4c) vs (2.4b)	-3.082 (0.998)	-3.271 (0.999)	-4.119 (0.999)	-4.17 (0.999)	-4.391 (0.999)	-4.174 (0.999)	-4.084 (0.999)	-3.939 (0.999)	-3.826 (0.999)	-3.679 (0.999)	-3.513 (0.999)	-3.266 (0.999)	-3.054 (0.998)	-2.845 (0.997)	-2.644 (0.995)	-2.457 (0.991)	-2.255 (0.986)	-2.072 (0.978)
	(2.4a) vs (2.4b)	-2.942 (0.998)	-2.626 (0.995)	-3.034 (0.998)	-2.297 (0.987)	-2.835 (0.997)	-2.477 (0.992)	-2.563 (0.993)	-2.454 (0.991)	-2.374 (0.989)	-2.224 (0.985)	-2.018 (0.976)	-1.838 (0.964)	-1.727 (0.955)	-1.603 (0.942)	-1.449 (0.923)	-1.304 (0.901)	-1.177 (0.878)	-1.05 (0.851)
	(2.4b) vs (2.4a)	4.34 (0.001**	4.117 (0.001**	4.356 (0.001**	3.703 (0.001**	4.13 (0.001**	3.814 (0.001**	3.978 (0.001**	3.913 (0.001**	3.876 (0.001**	3.694 (0.001**	3.5 (0.001**	3.285 (0.001**	3.12 (0.001**	2.944 (0.002**	2.779 (0.004**	2.623 (0.006**	2.462 (0.009**	2.294 (0.013**
Scenario B (2.6a)&(2.6 b)	(2.4a) vs (2.4c)	3 (0.002**	3.423 (0.001**	3.67 (0.001**	3.802 (0.001**	3.843 (0.001**	3.92 (0.001**	4.215 (0.001**	4.32 (0.001**	4.625 (0.001**	4.853 (0.001**	5.116 (0.001**	5.198 (0.001**	5.043 (0.001**	4.921 (0.001**	4.686 (0.001**	4.46 (0.001**	4.219 (0.001**	3.988 (0.001**
	(2.4c) vs (2.4a)	-0.602 (0.725)	-1.18 (0.879)	-2.008 (0.975)	-2.589 (0.994)	-2.727 (0.996)	-2.957 (0.998)	-3.257 (0.999)	-3.403 (0.999)	-3.701 (0.999)	-3.973 (0.999)	-4.292 (0.999)	-4.477 (0.999)	-4.511 (0.999)	-4.506 (0.999)	-4.357 (0.999)	-4.171 (0.999)	-3.977 (0.999)	-3.776 (0.999)
	(2.4b) vs (2.4c)	4.509 (0.001**	5.095 (0.001**	5.392 (0.001**	5.464 (0.001**	5.517 (0.001**	5.284 (0.001**	5.203 (0.001**	5.07 (0.001**	4.949 (0.001**	4.773 (0.001**	4.581 (0.001**	4.346 (0.001**	4.138 (0.001**	3.928 (0.001**	3.72 (0.001**	3.527 (0.001**	3.318 (0.001**	3.114 (0.002**
	(2.4c) vs (2.4b)	-3.325 (0.999)	-3.655 (0.999)	-4.472 (0.999)	-4.564 (0.999)	-4.765 (0.999)	-4.576 (0.999)	-4.516 (0.999)	-4.413 (0.999)	-4.321 (0.999)	-4.191 (0.999)	-4.037 (0.999)	-3.806 (0.999)	-3.597 (0.999)	-3.386 (0.999)	-3.183 (0.999)	-2.993 (0.998)	-2.781 (0.996)	-2.584 (0.994)
	(2.4a) vs (2.4b)	-2.85 (0.997)	-2.968 (0.998)	-3.322 (0.999)	-2.917 (0.998)	-3.137 (0.999)	-2.956 (0.998)	-2.98 (0.998)	-2.898 (0.997)	-2.788 (0.996)	-2.614 (0.994)	-2.387 (0.99)	-2.174 (0.983)	-2.022 (0.976)	-1.859 (0.966)	-1.682 (0.95)	-1.517 (0.932)	-1.364 (0.91)	-1.208 (0.883)
	(2.4b) vs (2.4a)	4.693 (0.001**	4.925 (0.001**	4.702 (0.001**	4.284 (0.001**	4.472 (0.001**	4.337 (0.001**	4.419 (0.001**	4.363 (0.001**	4.292 (0.001**	4.12 (0.001**	3.93 (0.001**	3.722 (0.001**	3.55 (0.001**	3.372 (0.001**	3.221 (0.001**	3.079 (0.002**	2.915 (0.003**	2.742 (0.004**

Scenario C (2.4a)	(2.6a) vs (2.5)	2.737 (0.004**	2.115 (0.019**	2.855 (0.003**	2.829 (0.003**	2.993 (0.002**	3.223 (0.001**	3.271 (0.001**	3.443 (0.001**	3.481 (0.001**	3.54 (0.001**	3.569 (0.001**	3.512 (0.001**	3.419 (0.001**	3.275 (0.001**	3.094 (0.002**	2.953 (0.002**	2.798 (0.004**	2.635 (0.006**
	(2.5) vs (2.6a)	-2.109 (0.981)	-1.562 (0.938)	-2.491 (0.992)	-2.482 (0.992)	-2.691 (0.995)	-2.977 (0.998)	-3.016 (0.998)	-3.217 (0.999)	-3.268 (0.999)	-3.359 (0.999)	-3.417 (0.999)	-3.399 (0.999)	-3.327 (0.999)	-3.199 (0.999)	-3.028 (0.998)	-2.905 (0.997)	-2.759 (0.996)	-2.606 (0.994)
Scenario D (2.4b)	(2.6b) vs (2.5)	2.677 (0.005**	3.503 (0.001**	3.797 (0.001**	3.941 (0.001**	4.067 (0.001**	4.125 (0.001**	4.175 (0.001**	4.201 (0.001**	4.19 (0.001**	4.17 (0.001**	4.137 (0.001**	4.041 (0.001**	3.906 (0.001**	3.751 (0.001**	3.595 (0.001**	3.46 (0.001**	3.287 (0.001**	3.1 (0.002**
	(2.5) vs (2.6b)	-2.148 (0.982)	-3.086 (0.998)	-3.329 (0.999)	-3.511 (0.999)	-3.658 (0.999)	-3.73 (0.999)	-3.79 (0.999)	-3.821 (0.999)	-3.818 (0.999)	-3.797 (0.999)	-3.769 (0.999)	-3.676 (0.999)	-3.544 (0.999)	-3.386 (0.999)	-3.228 (0.999)	-3.098 (0.998)	-2.929 (0.997)	-2.745 (0.996)

Table 2.9 TH: RMSFE under Scenarios A, B, and C

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
2.5	2.4a	0.013	0.021	0.032	0.042	0.051	0.058	0.064	0.068	0.072	0.074	0.077	0.080	0.083	0.088	0.092	0.096	0.101	0.105
	2.4b	0.017	0.025	0.037	0.046	0.057	0.065	0.072	0.077	0.082	0.085	0.089	0.093	0.098	0.103	0.108	0.113	0.118	0.123
	2.4c	0.012	0.019	0.029	0.036	0.044	0.050	0.055	0.059	0.061	0.063	0.065	0.067	0.070	0.073	0.076	0.080	0.084	0.088
2.6a	2.4a	0.014	0.021	0.033	0.043	0.052	0.060	0.066	0.071	0.075	0.078	0.082	0.085	0.089	0.094	0.099	0.104	0.110	0.115
	2.4c	0.013	0.020	0.030	0.039	0.047	0.054	0.060	0.064	0.067	0.070	0.072	0.075	0.079	0.083	0.087	0.091	0.096	0.100
2.6b	2.4b	0.017	0.026	0.039	0.049	0.061	0.070	0.078	0.084	0.090	0.095	0.100	0.105	0.111	0.117	0.123	0.130	0.136	0.143
	2.4c	0.013	0.020	0.030	0.039	0.047	0.054	0.060	0.064	0.067	0.070	0.072	0.075	0.079	0.083	0.087	0.091	0.096	0.100

Table 2.10 ID: Out-of-sample encompassing tests under the four scenarios

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
Scenario A (2.5)	(2.4a) vs (2.4c)	-0.47 (0.68)	-1.219 (0.886)	-2.337 (0.989)	-0.841 (0.798)	-0.96 (0.829)	-0.818 (0.792)	-0.914 (0.818)	-0.855 (0.802)	-0.708 (0.759)	-0.63 (0.734)	-0.501 (0.691)	-0.356 (0.638)	-0.28 (0.61)	-0.257 (0.601)	-0.274 (0.608)	-0.21 (0.583)	-0.154 (0.561)	-0.041 (0.516)
	(2.4c) vs (2.4a)	1.589 (0.059*	2.416 (0.009**	3.514 (0.001**	1.944 (0.028**	1.963 (0.027**	1.831 (0.036**	1.879 (0.033**	1.829 (0.036**	1.726 (0.045**	1.669 (0.05*	1.533 (0.066*	1.357 (0.09*	1.216 (0.115)	1.108 (0.137)	1.064 (0.146)	0.972 (0.168)	0.876 (0.193)	0.713 (0.24)
	(2.4b) vs (2.4c)	-1.338 (0.907)	-0.927 (0.821)	-0.59 (0.721)	0.853 (0.199)	2.417 (0.009**	2.688 (0.005**	2.637 (0.005**	2.684 (0.005**	2.856 (0.003**	3.079 (0.002**	3.17 (0.001**	3.206 (0.001**	3.197 (0.001**	3.037 (0.002**	2.84 (0.003**	2.62 (0.006**	2.388 (0.01**	2.078 (0.022**
	(2.4c) vs (2.4b)	2.284 (0.013**	1.876 (0.033**	1.544 (0.064*	0.01 (0.496)	-1.775 (0.96)	-2.103 (0.98)	-2.038 (0.977)	-2.073 (0.979)	-2.22 (0.985)	-2.4 (0.99)	-2.453 (0.991)	-2.544 (0.993)	-2.561 (0.993)	-2.433 (0.991)	-2.249 (0.985)	-2.044 (0.977)	-1.838 (0.964)	-1.525 (0.933)
	(2.4a) vs (2.4b)	1.436 (0.078*	1.016 (0.157)	0.23 (0.409)	-0.564 (0.713)	-1.984 (0.974)	-2.112 (0.98)	-2.058 (0.978)	-1.984 (0.974)	-1.965 (0.973)	-2.037 (0.977)	-1.999 (0.975)	-2.046 (0.977)	-1.968 (0.973)	-1.8 (0.961)	-1.648 (0.947)	-1.519 (0.932)	-1.353 (0.909)	-0.998 (0.838)
	(2.4b) vs (2.4a)	-0.603 (0.726)	-0.063 (0.525)	0.854 (0.198)	1.692 (0.048**	2.771 (0.004**	2.867 (0.003**	2.817 (0.003**	2.773 (0.004**	2.789 (0.004**	2.888 (0.003**	2.884 (0.003**	2.954 (0.002**	2.919 (0.003**	2.732 (0.004**	2.576 (0.007**	2.497 (0.008**	2.37 (0.011**	2.04 (0.024**
Scenario B (2.6a)&(2.6 b)	(2.4a) vs (2.4c)	-0.47 (0.68)	-1.219 (0.886)	-2.339 (0.989)	-0.85 (0.801)	-0.973 (0.833)	-0.836 (0.797)	-0.939 (0.824)	-0.889 (0.811)	-0.75 (0.772)	-0.681 (0.751)	-0.56 (0.711)	-0.421 (0.662)	-0.348 (0.635)	-0.324 (0.626)	-0.341 (0.633)	-0.278 (0.609)	-0.224 (0.588)	-0.109 (0.543)
	(2.4c) vs (2.4a)	1.589 (0.059*	2.417 (0.009**	3.516 (0.001**	1.952 (0.028**	1.974 (0.027**	1.845 (0.035**	1.897 (0.031**	1.854 (0.035**	1.755 (0.042**	1.703 (0.047**	1.574 (0.061*	1.404 (0.083*	1.266 (0.106)	1.158 (0.126)	1.113 (0.136)	1.023 (0.156)	0.93 (0.179)	0.769 (0.223)
	(2.4b) vs (2.4c)	-1.325 (0.905)	-1.014 (0.843)	-0.861 (0.804)	0.186 (0.427)	2.334 (0.012**	3.304 (0.001**	3.224 (0.001**	3.4 (0.001**	3.751 (0.001**	3.871 (0.001**	3.685 (0.001**	3.518 (0.001**	3.31 (0.001**	3.008 (0.002**	2.74 (0.004**	2.527 (0.007**	2.323 (0.012**	2.026 (0.024**
	(2.4c) vs (2.4b)	2.205 (0.016**	1.834 (0.036**	1.625 (0.055*	0.615 (0.271)	-1.136 (0.87)	-1.994 (0.975)	-1.96 (0.973)	-2.103 (0.98)	-2.354 (0.989)	-2.459 (0.991)	-2.319 (0.988)	-2.312 (0.988)	-2.191 (0.983)	-1.969 (0.973)	-1.736 (0.956)	-1.539 (0.935)	-1.35 (0.908)	-1.057 (0.852)
	(2.4a) vs (2.4b)	1.304 (0.099*	0.97 (0.168)	0.396 (0.347)	-0.117 (0.546)	-1.478 (0.928)	-1.672 (0.95)	-1.756 (0.958)	-1.73 (0.955)	-1.726 (0.955)	-1.77 (0.959)	-1.699 (0.952)	-1.676 (0.95)	-1.529 (0.934)	-1.32 (0.904)	-1.134 (0.869)	-0.97 (0.831)	-0.802 (0.787)	-0.512 (0.695)
	(2.4b) vs (2.4a)	-0.519 (0.697)	-0.106 (0.542)	0.634 (0.264)	1.313 (0.097*	2.509 (0.007**	2.736 (0.004**	2.876 (0.003**	2.946 (0.002**	3.037 (0.002**	3.142 (0.001**	3.107 (0.002**	3.116 (0.001**	2.985 (0.002**	2.719 (0.004**	2.526 (0.007**	2.385 (0.011**	2.225 (0.015**	1.921 (0.03**

Scenario C (2.4a)	(2.6a) vs (2.5)	-	-1.791 (0.961)	-1.485 (0.929)	-0.874 (0.807)	-0.405 (0.657)	-0.156 (0.562)	-0.255 (0.6)	-0.42 (0.662)	-0.43 (0.666)	-0.442 (0.67)	-0.562 (0.712)	-0.598 (0.724)	-0.6 (0.724)	-0.437 (0.668)	-0.251 (0.599)	-0.21 (0.583)	-0.216 (0.585)	-0.275 (0.608)
	(2.5) vs (2.6a)	-	1.795 (0.039**	1.493 (0.07*	0.886 (0.19)	0.424 (0.337)	0.184 (0.427)	0.292 (0.386)	0.466 (0.322)	0.486 (0.314)	0.508 (0.307)	0.637 (0.263)	0.678 (0.25)	0.686 (0.248)	0.525 (0.301)	0.339 (0.368)	0.304 (0.381)	0.311 (0.379)	0.374 (0.355)
Scenario D (2.4b)	(2.6b) vs (2.5)	1.438 (0.078*	-0.112 (0.544)	-0.924 (0.82)	-1.329 (0.906)	-1.509 (0.932)	-1.478 (0.928)	-1.368 (0.912)	-1.257 (0.893)	-1.113 (0.865)	-1.011 (0.842)	-0.827 (0.794)	-0.712 (0.76)	-0.561 (0.711)	-0.476 (0.682)	-0.387 (0.65)	-0.303 (0.618)	-0.228 (0.59)	-0.095 (0.538)
	(2.5) vs (2.6b)	-1.237 (0.89)	0.372 (0.356)	1.223 (0.113)	1.563 (0.062*	1.693 (0.048**	1.663 (0.051*	1.572 (0.061*	1.469 (0.074*	1.337 (0.093*	1.262 (0.106)	1.116 (0.135)	1.026 (0.155)	0.905 (0.185)	0.84 (0.203)	0.759 (0.226)	0.677 (0.251)	0.601 (0.276)	0.462 (0.323)

Table 2.11 ID: RMSFE under Scenarios A, B, and C

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
2.5	2.4a	0.040	0.070	0.093	0.111	0.124	0.131	0.134	0.134	0.131	0.126	0.122	0.122	0.122	0.124	0.126	0.128	0.131	0.133
	2.4b	0.038	0.069	0.094	0.115	0.132	0.141	0.145	0.146	0.144	0.140	0.137	0.137	0.137	0.138	0.140	0.142	0.144	0.144
	2.4c	0.041	0.072	0.097	0.114	0.127	0.135	0.137	0.138	0.135	0.130	0.126	0.125	0.125	0.126	0.128	0.131	0.133	0.135
2.6a	2.4a	0.040	0.070	0.093	0.111	0.124	0.131	0.134	0.133	0.130	0.125	0.122	0.121	0.122	0.123	0.125	0.128	0.131	0.133
	2.4c	0.041	0.072	0.097	0.114	0.127	0.135	0.138	0.138	0.135	0.130	0.126	0.125	0.125	0.126	0.128	0.131	0.133	0.135
2.6b	2.4b	0.038	0.069	0.093	0.113	0.129	0.138	0.142	0.143	0.141	0.137	0.134	0.134	0.135	0.136	0.138	0.140	0.142	0.143
	2.4c	0.041	0.072	0.097	0.114	0.127	0.134	0.137	0.137	0.135	0.130	0.126	0.125	0.125	0.126	0.128	0.130	0.133	0.134

Table 2.12 MA: Out-of-sample encompassing tests under the four scenarios

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
Scenario A (2.5)	(2.4a) vs (2.4c)	8.3 (0.001**	8.923 (0.001**	9.167 (0.001**	9.622 (0.001**	8.926 (0.001**	9.12 (0.001**	8.92 (0.001**	8.566 (0.001**	8.137 (0.001**	7.739 (0.001**	7.333 (0.001**	6.861 (0.001**	6.44 (0.001**	6.001 (0.001**	5.622 (0.001**	5.26 (0.001**	4.839 (0.001**	4.456 (0.001**
	(2.4c) vs (2.4a)	-7.59 (0.999)	-8.133 (0.999)	-8.213 (0.999)	-8.313 (0.999)	-7.554 (0.999)	-7.543 (0.999)	-7.299 (0.999)	-6.954 (0.999)	-6.596 (0.999)	-6.281 (0.999)	-5.962 (0.999)	-5.599 (0.999)	-5.274 (0.999)	-4.932 (0.999)	-4.64 (0.999)	-4.358 (0.999)	-4.023 (0.999)	-3.709 (0.999)
	(2.4b) vs (2.4c)	10.51 (0.001**	10.494 (0.001**	10.202 (0.001**	9.902 (0.001**	9.702 (0.001**	9.434 (0.001**	9.124 (0.001**	8.785 (0.001**	8.361 (0.001**	7.971 (0.001**	7.609 (0.001**	7.191 (0.001**	6.787 (0.001**	6.363 (0.001**	5.984 (0.001**	5.606 (0.001**	5.21 (0.001**	4.851 (0.001**
	(2.4c) vs (2.4b)	-9.501 (0.999)	-9.228 (0.999)	-8.967 (0.999)	-8.608 (0.999)	-8.262 (0.999)	-7.97 (0.999)	-7.618 (0.999)	-7.255 (0.999)	-6.772 (0.999)	-6.339 (0.999)	-5.962 (0.999)	-5.521 (0.999)	-5.097 (0.999)	-4.665 (0.999)	-4.29 (0.999)	-3.932 (0.999)	-3.559 (0.999)	-3.204 (0.999)
	(2.4a) vs (2.4b)	-9.501 (0.999)	-9.228 (0.999)	-8.967 (0.999)	-8.608 (0.999)	-8.262 (0.999)	-7.97 (0.999)	-7.618 (0.999)	-7.255 (0.999)	-6.772 (0.999)	-6.339 (0.999)	-5.962 (0.999)	-5.521 (0.999)	-5.097 (0.999)	-4.665 (0.999)	-4.29 (0.999)	-3.932 (0.999)	-3.559 (0.999)	-3.204 (0.999)
	(2.4b) vs (2.4a)	10.213 (0.001**	10.245 (0.001**	9.9 (0.001**	9.466 (0.001**	9.329 (0.001**	9 (0.001**	8.632 (0.001**	8.246 (0.001**	7.794 (0.001**	7.374 (0.001**	6.979 (0.001**	6.545 (0.001**	6.13 (0.001**	5.711 (0.001**	5.334 (0.001**	4.971 (0.001**	4.599 (0.001**	4.251 (0.001**
Scenario B (2.6a)&(2.6 b)	(2.4a) vs (2.4c)	8.3 (0.001**	8.816 (0.001**	8.892 (0.001**	9.166 (0.001**	8.845 (0.001**	8.958 (0.001**	8.565 (0.001**	8.202 (0.001**	7.845 (0.001**	7.467 (0.001**	7.068 (0.001**	6.631 (0.001**	6.171 (0.001**	5.797 (0.001**	5.469 (0.001**	5.073 (0.001**	4.649 (0.001**	4.309 (0.001**
	(2.4c) vs (2.4a)	-7.59 (0.999)	-7.941 (0.999)	-7.849 (0.999)	-7.856 (0.999)	-7.482 (0.999)	-7.457 (0.999)	-7.085 (0.999)	-6.771 (0.999)	-6.476 (0.999)	-6.164 (0.999)	-5.846 (0.999)	-5.501 (0.999)	-5.137 (0.999)	-4.843 (0.999)	-4.586 (0.999)	-4.268 (0.999)	-3.922 (0.999)	-3.639 (0.999)
	(2.4b) vs (2.4c)	10.193 (0.001**	10.068 (0.001**	9.733 (0.001**	9.385 (0.001**	9.11 (0.001**	8.771 (0.001**	8.412 (0.001**	8.029 (0.001**	7.586 (0.001**	7.197 (0.001**	6.854 (0.001**	6.493 (0.001**	6.14 (0.001**	5.764 (0.001**	5.443 (0.001**	5.123 (0.001**	4.776 (0.001**	4.451 (0.001**
	(2.4c) vs (2.4b)	-9.426 (0.999)	-9.17 (0.999)	-8.915 (0.999)	-8.526 (0.999)	-8.125 (0.999)	-7.781 (0.999)	-7.367 (0.999)	-6.911 (0.999)	-6.351 (0.999)	-5.861 (0.999)	-5.453 (0.999)	-5.016 (0.999)	-4.593 (0.999)	-4.163 (0.999)	-3.802 (0.999)	-3.464 (0.999)	-3.113 (0.998)	-2.774 (0.998)
	(2.4a) vs (2.4b)	-9.939 (0.999)	-9.77 (0.999)	-9.436 (0.999)	-9.026 (0.999)	-8.667 (0.999)	-8.157 (0.999)	-7.589 (0.999)	-6.888 (0.999)	-6.158 (0.999)	-5.528 (0.999)	-4.931 (0.999)	-4.324 (0.999)	-3.757 (0.999)	-3.212 (0.999)	-2.753 (0.996)	-2.351 (0.989)	-1.974 (0.973)	-1.626 (0.945)
	(2.4b) vs (2.4a)	10.213 (0.001**	10.239 (0.001**	9.795 (0.001**	9.198 (0.001**	8.891 (0.001**	8.395 (0.001**	7.905 (0.001**	7.355 (0.001**	6.778 (0.001**	6.246 (0.001**	5.769 (0.001**	5.301 (0.001**	4.853 (0.001**	4.418 (0.001**	4.031 (0.001**	3.689 (0.001**	3.361 (0.001**	3.045 (0.002**

Scenario C (2.4a)	(2.6a) vs (2.5)	-	-	0.552 (0.292)	1.054 (0.148)	1.302 (0.099*	1.367 (0.088*	1.252 (0.108)	1.282 (0.103)	1.428 (0.08*	1.417 (0.081*	1.396 (0.084*	1.405 (0.083*	1.43 (0.079*	1.414 (0.082*	1.338 (0.093*	1.246 (0.109)	1.139 (0.13)	1.027 (0.155)
	(2.5) vs (2.6a)	-	0.56 (0.289)	0.705 (0.242)	0.429 (0.335)	0.37 (0.356)	0.455 (0.325)	0.634 (0.264)	0.606 (0.274)	0.446 (0.329)	0.446 (0.329)	0.436 (0.332)	0.374 (0.355)	0.275 (0.392)	0.23 (0.41)	0.265 (0.396)	0.294 (0.385)	0.323 (0.374)	0.365 (0.358)
Scenario D (2.4b)	(2.6b) vs (2.5)	-	10.226 (0.001**	9.766 (0.001**	9.203 (0.001**	8.94 (0.001**	8.482 (0.001**	7.996 (0.001**	7.5 (0.001**	6.957 (0.001**	6.454 (0.001**	6.013 (0.001**	5.588 (0.001**	5.184 (0.001**	4.784 (0.001**	4.43 (0.001**	4.11 (0.001**	3.786 (0.001**	3.476 (0.001**
	(2.5) vs (2.6b)	-	-9.822 (0.999)	-9.468 (0.999)	-8.996 (0.999)	-8.67 (0.999)	-8.149 (0.999)	-7.561 (0.999)	-6.911 (0.999)	-6.187 (0.999)	-5.496 (0.999)	-4.889 (0.999)	-4.297 (0.999)	-3.735 (0.999)	-3.19 (0.999)	-2.719 (0.995)	-2.325 (0.988)	-1.957 (0.972)	-1.609 (0.943)

Table 2.13 MA: RMSFE under Scenarios A, B, and C

		1 step	2 step	3 step	4 step	5 step	6 step	7 step	8 step	9 step	10 step	11 step	12 step	13 step	14 step	15 step	16 step	17 step	18 step
2.5	2.4a	0.022	0.031	0.038	0.047	0.052	0.058	0.063	0.067	0.071	0.074	0.077	0.080	0.082	0.085	0.087	0.089	0.090	0.091
	2.4b	0.073	0.096	0.105	0.109	0.112	0.114	0.115	0.116	0.116	0.117	0.117	0.118	0.119	0.120	0.120	0.122	0.122	0.121
	2.4c	0.012	0.018	0.023	0.030	0.035	0.040	0.045	0.049	0.052	0.055	0.058	0.061	0.064	0.066	0.069	0.072	0.074	0.075
2.6a	2.4a	0.022	0.031	0.038	0.047	0.053	0.059	0.064	0.068	0.072	0.076	0.079	0.082	0.085	0.087	0.090	0.092	0.093	0.093
	2.4c	0.012	0.018	0.023	0.030	0.035	0.040	0.045	0.049	0.052	0.055	0.059	0.062	0.065	0.068	0.070	0.073	0.075	0.076
2.6b	2.4b	0.073	0.096	0.104	0.108	0.110	0.111	0.112	0.112	0.112	0.112	0.113	0.113	0.114	0.114	0.114	0.115	0.115	0.114
	2.4c	0.012	0.018	0.023	0.029	0.035	0.039	0.043	0.047	0.050	0.053	0.056	0.058	0.061	0.063	0.065	0.067	0.069	0.070

Table 2.14 Summary from Table 2.2 to Table 2.13

	Scenario A 2.5	Scenario B 2.6a	Scenario B 2.6b	Scenario B 2.6a&2.6b	Scenario C 2.4a	Scenario D 2.4b
SG	(4c)<(4b)><(4a)	(4b)><(4a)	(4c)<(4a)	(4c)<(4b)	(2.6a)><(2.5)	(2.6b)><(2.5)
KOR	(4c)<(4a)<(4b)	(4a)<(4b)	(4c)<(4a)	(4c)<(4b)	(2.5)<(2.6a)	(2.5)<(2.6b)
TW	(4a)<(4c)<(4b)	(4a)<(4b)	(4c)<(4a)	(4b)<(4c)	(2.6a)<>(2.5)	(2.6b)<>(2.5)
TH	(4c)<(4b)<(4a)	(4b)<(4a)	(4c)<(4a)	(4c)<(4b)	(2.6a)<(2.5)	(2.6b)<(2.5)
ID	(4b)>(4a),(4a)<>(4c),(4b)<>(4c)	(4a)<(4b)	(4c)><(4a)	(4b)<>(4c)	(2.5)<(2.6a)	(2.6b)<>(2.5)
MA	(4c)<(4b)<(4a)	(4b)<(4a)	(4c)<(4a)	(4c)<(4b)	(2.6a)<(2.5)	(2.6b)<(2.5)

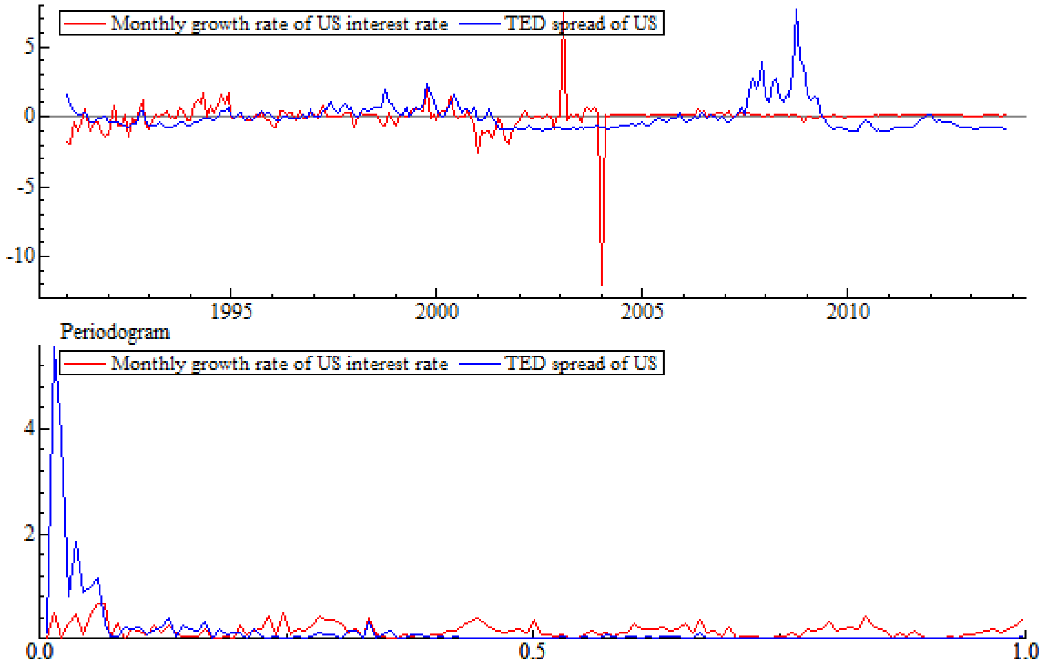

Figure 2.1 Time series plot (upper part) and Periodogram (lower part) of TED spread and monthly growth rate of the interest rate of the US.

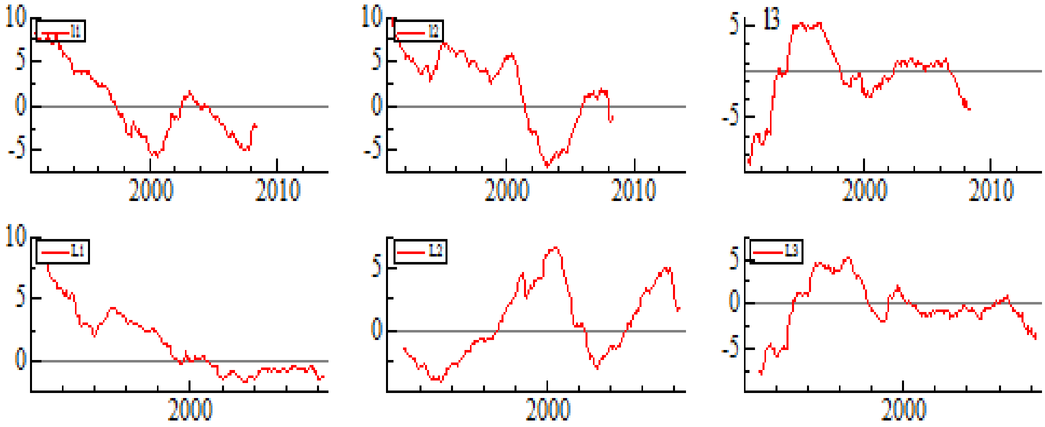

Figure 2.2 Dynamics of subsample and full sample estimated long-run FCIs

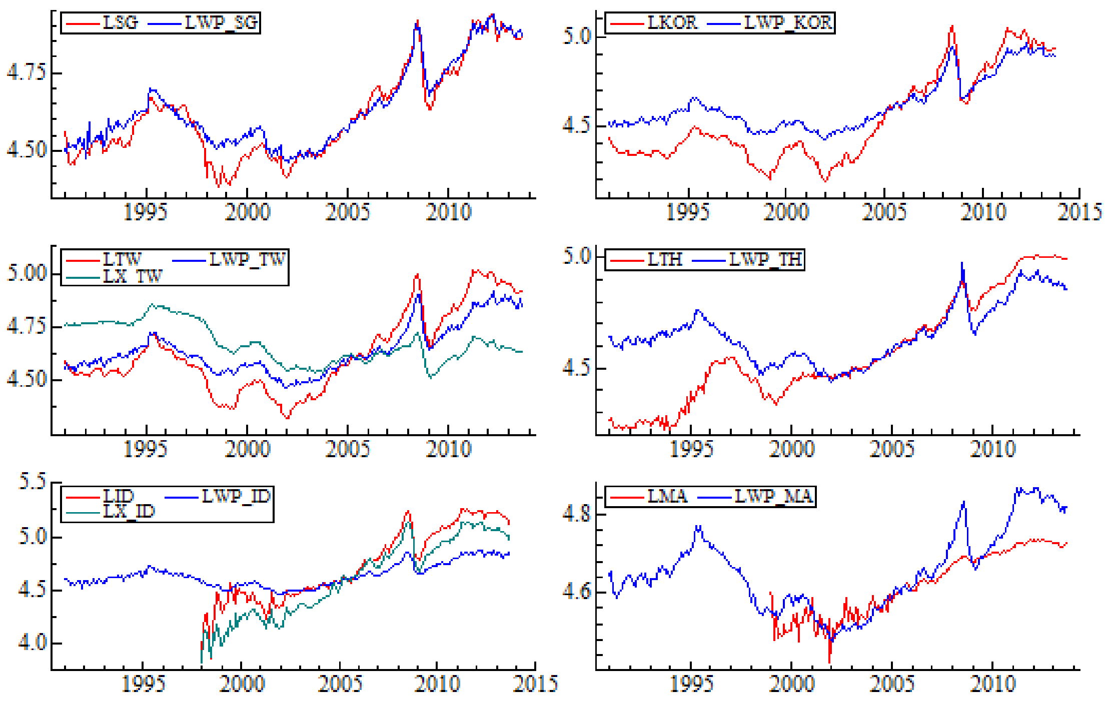

Figure 2.3 Time series plot of import price index (L{country}), world export price index (LWP_{country}) and domestic export price index (LX_{country})

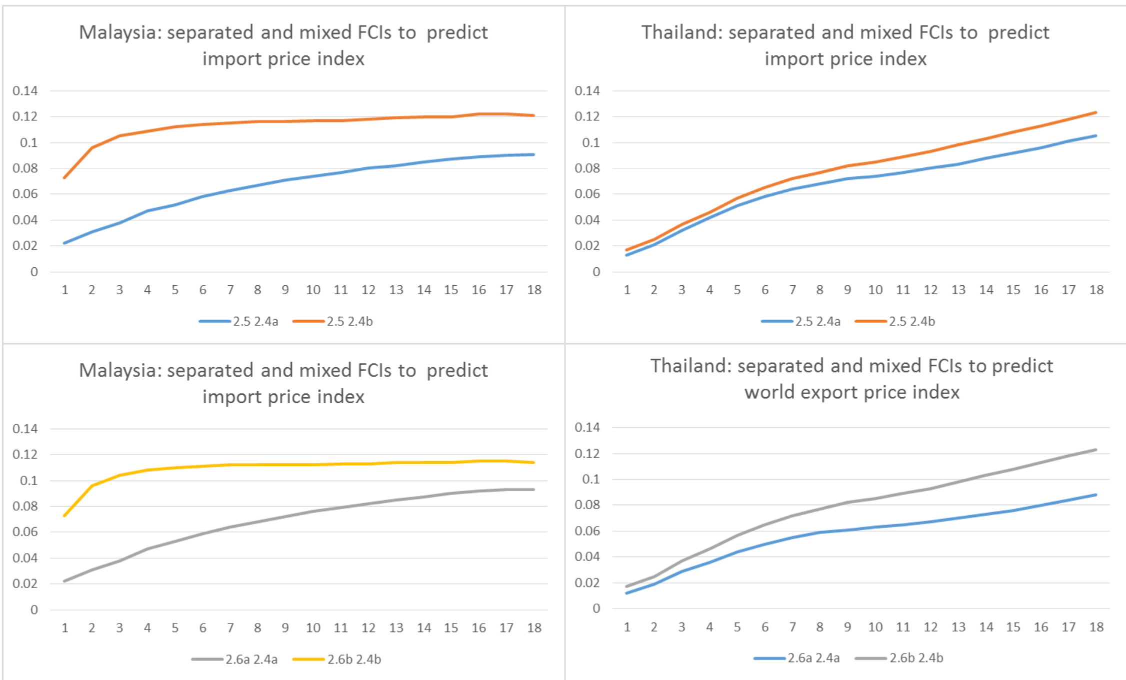

Figure 2.4 MSFE along with the expansion of forecasting horizon

Chapter 3 A Fixed-weighted PLS-R Approach

3.1 Introduction

This chapter uses Partial Least Squares Regression (PLS-R),[42] one of the two methodologies belonging to PLS, to estimate FCIs, and compares the predictive power of PLS-R FCIs with PCA FCIs. In addition, in this chapter both the PLS-R FCIs and PCA FCIs are fixed-weighted.

The fixed-weights approach is adopted in this chapter as a reflection of recent literature on the study of a composite variable. Rigdon (2014) argued that any latent variable should represent a 'real entity'. Lee and Cadogan (2013, xx) further argued that 'allowing an algorithm to determine indicator weightings is dangerous because it reduces the ability of the research community to compare research findings across studies: the weights obtained 'are often context dependent' and they proposed a more comparable alternative: using a constant weighting composite variable. Howell (2013, xx) also added that fixed weights are the best alternative 'when the weights used to form the composite are part of the composite variable's definition, . . ., and when the composite is an identity.'

In the context of this research, FCIs reflect the current state of financial variables that influence the future state of the economy and the weights used to form FCIs entail important implications. In the literature of FCIs estimated by DFM, although the disaggregate contribution (component of the aggregate FCIs) to the forecasting performance is widely discussed, their FCIs have time-varying weights due to the DFM-estimating approach. (See subsection 2.1.2) As a result, most of disaggregate analyses in the literature of FCIs are far from being conclusive.

It is in this sense that FCIs are fixed weighted in this chapter. Specifically, the in-sample, estimated weights of both the PLS-R and PCA FCIs are held fixed for the whole out-of-sample period. In this way, FCIs can be decomposed, and the disaggregate analysis can be carried out.

The recursively estimated and forecasted FCIs (see subsection 2.2.1) are not used in this chapter because the analysis at the disaggregate level cannot be carried out. A comparison between the fixed-weighted FCIs and the recursively estimated and forecasted FCIs can help explain this point. As to fixed-weighted FCIs, the disaggregate analysis can be easily carried out by using in-sample, estimated weights because they are the same as the out-of-sample ones.

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[42] There are in general two PLS methodologies. Since the other methodology of PLS, the PLS path modelling, is only used in Chapter 5, this chapter will only introduce PLS-R.

As to recursively estimated and forecasted FCIs, however, it is difficult to conduct the disaggregate analysis by using the in-sample, estimated weights. As subsection 2.2.1 shows, although the FCIs are held fixed in-sample, the out-of-sample FCIs are recursively estimated along with the recursive predictive test. In this sense, (1) the in-sample weight estimates are irrelevant to the out-of-sample ones and; (2) the out-of-sample forecasted weights vary along with the recursive predictive test.

Fixed-weighted FCIs estimated by PCA ('fixed-weighted' is henceforth omitted for PCA FCIs and the following PLS-R FCIs because weights are fixed for both types of FCIs in this chapter) are used as to replace FCIs estimated by DFM, because PCA FCIs have similar dynamics with DFM FCIs and weights can be much more easily estimated when FCIs are estimated by PCA (compared to DFM). This argument can be explained by the Kalman filter method used in the estimated final DFM FCIs. First, the Kalman filter functions purely as a smoother, so it keeps the general dynamics of the initial factors, the PCA factors (see subsection 2.2.1).[43] Second, when the factor loadings (of final DFM factors) are smoothed by the Kalman filter, they cannot map one-to-one the weight estimates at disaggregate level; see Harvey (1990). By contrast, the factor-loading matrix of PCA FCIs is simply the transposition of the weight matrix.

As will be shown in Section 3.2, PCA FCIs reflect the covariance within the financial indicators matrix, and therefore FCIs estimated by PCA are under the challenge that they may include too much noisy information. That is, some external financial indicators that move irrelevant to target variable may be given a large weight in constructing FCIs.

As an alternative method to solve this issue, PLS-R[44] was proposed by Wold et al. (1984). As addressed by Wold et al. (2001b, 109), PLS-R is 'a recently developed generalization of multiple linear regressions. Unlike MLR, it can analyse data with strongly collinear (correlated), noisy, and numerous X-variables, and it can also simultaneously model several response variables, Y'.[45] In a word, PLS-R has an advantage over PCA in that it takes account of the correlation of target variable and predictors in the dimension-reduction process. Due to the experimental design that targets multiple economies, multiple PLS-R FCIs are constructed, that is, economic-specific FCIs, as compared to the single PCA FCIs that are identical to all target economies. And

[43] Stock and Watson (2011) have mathematically proven that when the subset of balanced data has a high dimension, initial factor and factor loadings can be estimated by PCA.

[44] A literature review of PLS shows that there are two general PLS methodologies—PLS-R and PLS path modelling. Since this chapter focuses on PLS-R FCIs, only PLS-R is elaborated in this chapter. PLS path modelling will be elaborated in the introduction to chapter 5.

[45] In practice, the econometric field has widely used chemometrics data; see Wold et al. (1984); Wold et al. (2001b),; however, only recent literature shows a strong interest in following PLS-R for a dimension-reduction purpose, such as Chun and Keleş (2010); Fuentes et al. (2014b); and Lannsjö (2014); Kapetanios et al. (2015).

if the PLS-R FCIs can more efficiently filter out noisy data at the disaggregate level (than PCA FCIs), the PLS-R FCIs' forecasting model should outperform the PCA FCIs' forecasting model and may even outperform the benchmark forecasting model specified in Chapter 2 across all target economies.

Three main hypotheses are raised subsequently in order to test which type of FCIs (PCA vs. PLS-R) have better predictive power.

1) FCIs aggregated from long-run indicators have better predictive power than those aggregated from short-run indicators;[46]
2) PLS-R FCIs have better predictive power than those with weight estimated by PCA FCIs;

Both PCA and PLS-R FCIs turn into noise rather than signal in predicting a target variable during the 2008 crisis. This hypothesis is proposed based on the postulation that a large location shift may have occurred to FCIs during the 2008 crisis. (M. P. Clements and Hendry 2011)

The following Sections are organized as follows: Section 3.2 introduces the PLS-R methodology and shows how they are incorporated into the final forecasting model; Section 3.3 discusses the experimental design related to the test of the three hypotheses; Section 3.4 discusses the empirical results by showing that they support the three hypotheses; Section 3.5 further compares the disaggregated predictive power of financial indicators with weight-estimated by PLS-R; and Section 3.6 concludes with main findings, both at aggregate and disaggregate level.3.2 PLS-R vs. PCA and related FCIs' forecasting models

3.2 PLS-R vs. PCA and related FCIs' forecasting models

This section's primary task is to show methodologically how PLS-R differs from PCA and how PCA FCIs and PLS-R FCIs include a final forecasting model as leading indicators. Two subsections are listed for this purpose. Subsection 3.2.1 explains the methodological difference between PLS-R and PCA by showing that PLS-R reflects the covariance between the target variable and predictors, that is, the import price index and financial indicator matrix, while PCA reflects the covariance within the financial indicator matrix. Subsection 3.2.2 lists the PCA FCIs' forecasting models and the two types of PLS-R FCIs' forecasting models.

[46] For the definition of long-run and short-run indicators, please refer to the last chapter.

3.2.1 Methodological difference between PCA and PLS

PLS-R differs from PCA in terms of residual minimization. According to Geladi and Kowalski (1986), the difference in residual minimization can be illustrated by a matrix form of a two-pass regression model.

$$X = FV' + \epsilon \quad (3.1)$$

$$Y = UC' + u \quad (3.2)$$ [47]

Here, X denotes the financial indicator matrix and Y denotes the target variable—the import price index of a target economy. In the context of PCA, only Equation (3.1) is used to estimate principal components (FCIs). Here, F denotes a matrix composed of a first few PCA principal components and V, the corresponding factor=loading matrix.

By minimizing the residual vector ϵ, PCA rotates from the original X coordinate system to the system defined by principal components axes. According to Massy (1965,235), the principal components of PCA are orthogonal to each other, and they are supposed to capture the variance–covariance of financial indicator matrix, X, that is, X^TX, following a descending order—the first principal component captures the largest variance of X; the second principal component captures the second largest variance of X, and so on.

By contrast, in the context of PLS-R, Equations (3.1) and (3.2) are both used to estimate principal components of PLS-R: F and V now, respectively, denote a matrix composed of the first few PLS-R principal components and factor loadings of X , while U and C denote the principal components and factor loadings of Y. Unlike PCA, it is now by minimizing the residual u that principal components of PLS-R capture the covariance between Y and X, that is, X^TY^TYX, following the descending order.

According to Göteborg (2014), PLS-R, at its origin, does not specify dynamics. This chapter, however, models the leading role of PLS-R FCIs from a dynamic re-specification of Equations (3.1) – (3.2).

[47] Variables in all equations of this section are in matrix form but with a dimension subscript omitted for clarity.

$$X_{t-1} = FV' + \epsilon \tag{3.1'}$$

$$Y_t = UC' + u \tag{3.2'}$$

From Equations (3.1') and (3.2'), principal components of PLS-R capture the covariance between Y_t and X_{t-1}, that is, $X_{t-1}^T Y_t^T Y_t X_{t-1}$.

The previous discussion only shows the estimation process of the first PLS-R factor. The more detailed estimation process for the first few PCA and PLS-R factors and their differences are discussed in Appendix 3A.

3.2.2 PCA, PLS-R y-predicted and PLS-R r-predicted FCIs' forecasting models

This subsection lists three types of FCIs' forecasting models—one PCA and two PLS-R FCIs' forecasting models—to be used in the following empirical analysis. First, a two-step approach is adopted to construct PCA FCIs' forecasting model.

Step 1 (PCA step)

$$X_t = F_{PCA,t}V' + \epsilon \tag{3.3}$$

Step 2 is the (final forecasting model)

$$Y = X_{macro}\mathrm{B}_{macro} + A(L)F_{PCA,t}B_{PCA} + e \tag{3.4}$$

X_{macro} denotes domestic macro predictors, that is, the domestic export price index, exchange rate, and the world export price index. B_{macro} and B_{PCA} are coefficients of X_{macro} and F_{PC}^{sur} to be estimated. $A(L)$ is the lag operator without a constant term. In this way, the PCA factors, the leading role of PCA FCIs, **i**s expressed in only their lagged form that is allowed to be included in the final forecasting model. Second, a similar two-step approach is adopted to construct PLS-R y-predicted FCIs' forecasting models.

Step 1 (PLS step)

$$\begin{cases} X_{t-1} = {}^{pls}FV' + \epsilon \\ Y_t = UC' + u \end{cases} \tag{3.5}$$

Step 2 (final forecasting model)

$$Y = X_{macro}\mathrm{B}_{macro} + A'(L)^{pls}FB_{PLS} + e_A \tag{3.6}$$

The Equation set (3.5) is identical to Equations (3.1') – (3.2'). ${}^{pls}F$ denotes PLS-R y-predicted FCIs ('y-predicted' indicates that the target is used to estimate PLS-R FCIs) and they reflect the covariance matrix between the contemporaneous import price index and the 1-month lagged financial indicator matrix, the $X_{t-1}^T Y_t^T Y_t X_{t-1}$. Third, a three-step approach is adopted to construct PLS-R r-predicted FCIs' forecasting models.

Step 1

$$Y = X_{macro}\mathrm{B}_{macro} + u_B \tag{3.7}$$

Step 2 (PLS step)

$$\begin{cases} X_{t-1} = {}^{pls}_{resid}FV' + \epsilon \\ \hat{u}_{B_t} = UC' + u \end{cases} \tag{3.8}$$

Here, $\hat{u}_{B_t}$ is the estimated residual from Equation (3.7) in Step 1, and ${}^{pls}_{resid}F$ denoting PLS-R r-predicted FCIs ('r-predicted' indicates that the residual of the benchmark forecasting model is used to estimate PLS-R principal components).

Step 3 (final forecasting model)

$$Y = X_{macro}\mathrm{B}_{macro} + A''(L)\,{}^{pls}_{resid}FB_{PLS} + e_B \tag{3.9}$$

Unlike PLS-R y-predicted FCIs, PLS-R r-predicted FCIs reflect the covariance between residuals from the benchmark forecasting model (without FCIs) and financial indicator matrix X, that is, $\hat{u}_{B_{t-1}}^T Y_t^T Y_t \hat{u}_{B_{t-1}}$. The idea of PLS-R r-predicted FCIs originates from a finding in Chapter 2—the macro predictors contribute major explanatory power in-sample and major predictive power out-of-sample while FCIs contribute marginal power. Because PLS-R r-predicted FCIs can concentrate on the marginal residual information that hasn't been explained by macro predictors, they may contain useful predictive information that does not overlap with the macro predictors.

3.3 Experimental design

Since Chapter 2 shows that separated FCIs have better forecasting performance than mixed FCIs, this chapter shall only focus on the PCA and PLS-R FCIs (both y-predicted and r-predicted) constructed from the four separated sets, long-run, monthly short-run, quarterly short-run, and annual short-run indicator sets.

A more meticulous comparison of long-run FCIs (from the long-run indicator set) and short-run FCIs (from the three short-run indicator sets) is necessary because the use of both long-run and short-run indicators may disturb the comparison the PLS-R and PCA FCIs. For example, when comparing a monthly short-run PLS-R FCIs' forecasting model to a long-run PCA FCIs' forecasting model, the difference in forecasting performance may rather be attributed to the difference between monthly short-run FCIs and level long-run FCIs than be attributed to the different weight-estimating method (PCA vs. PLS-R). In addition, long-run indicators reflect the external market misalignment information and, therefore, are supposed to carry more predictive information than short-run indicators.

This section first elaborates some adjustments of long-run and short-run indicator sets, which are also used for Chapter 4 and Chapter 5. Other new experimental designs, especially related to the three hypotheses, are then discussed.

3.3.1 Adjusted long-run and short-run indicator sets

The adjusted long-run and short-run indicator sets are shown in Appendix 3B. In general, the adjustment of the long-run and short-run indicator set is due to three reasons.

First, unlike DFM,[48] PCA cannot deal with an unbalanced data set, long-run indicators such as LOIS variables (the LIBOR-OIS spread) and the equity index variables that measure the proportion of financial industry to total industry are deleted from the long-run indicator set due to their relative short history (officially collected in the database).[49] For the same reason, short-run indicators such as growth rate of futures index are also deleted.

Second, in order to make up for the deleted indicators, (as otherwise indicators will be too short to aggregate), new types of both long-run and short-run indicators are used. In this chapter, long-run Indicators measuring the market misalignment within the derivative market, between the money market and the bond market, between the housing market and the equity

[48] Specifically, it is the Kalman filter to deal with missing data in the unbalanced data set.

[49] In the database of CEIC and DataStream, for example, LOIS variables can only be traced back to 1999M7 and, therefore, cannot be used to construct PCA or PLS-R FCIs starting from 1991M1.

market are added to the long-run indicator set, and the growth rate of government bonds (short-run indicators) are added to the short-run indicator set.

Third, more quantitative indicators and indicators from Japan's financial market are included in the adjusted long-run indicator set. The inclusion of quantity indicators reflects the concern of Hatzius et al. (2010, 26) that the 2008 crisis makes the quantity financial indicators more important than they have been in the past, compared to the price indicators. The inclusion of Japanese financial market indicators actually reflects the geographic link between the six target economies and the exporting economies. As from Figure 3.1, regarding the six target economies, the import volume from Japan amounts to over 20%, a proportion much higher than average. Furthermore, the geographic disaggregate analysis to be carried out in Section 3.5 can benefit from the more evenly distributed long-run indicators in terms of geographic location due to the additionally included indicators from the Japanese financial market. (Previously there are not as many Japan financial indicators as those of other financial markets).

It is worth mentioning that the use of PCA FCIs threatens the experiment because their first factors do not necessarily survive in the final forecasting model. In fact, the chances are high that they may drop off. Taking long-run factors estimated by DFM in Chapter 2, as an example, the first long-run factor is only in-sample significant with respect to Taiwan and Thailand. Because of the similarity in dynamics between DFM and PCA FCIs, PCA FCIs may also drop off. Empirically, Table 3.1 shows that the first factors survive[56] in the final forecasting model with respect to all six target economies, and, therefore, the forecasting performance of long-run FCIs and short-run FCIs can be successfully carried out.

3.3.2 Other key issues

In order to make the tests on the three hypotheses more accurate and practical, this chapter revises multiple key settings used in Chapter 2.

First, this chapter limits the usage of first PCA and PLS-R (y-predicted and r-predicted) factor. As noted by Gadanecz and Jayaram (2008), it is desirable for central banks to construct single aggregated FCIs to measure the financial stability as a whole. This chapter only allows one indicator set, either the single long-run or three short-run indicators set, to be used to construct a single first factor.

[56] This is probably because several key settings in this chapter differ from Chapter 2: (1) limiting the usage of first factor such that second and third factors can no longer substitute for the first factor (substitutive effect); and (2) narrowing down of the in-sample period as is to be exhibited in Section 3.2.3.

Second, instead of setting the forecasting horizon up to 18-months ahead, this chapter narrows it down to up to 6-months ahead, because based on common sense, the information of the external financial market should be fully absorbed by the domestic market.

Third, in order to simplify the empirical analysis, the peripheral forecasting models used to predict macro predictors are only AR models, namely without FCIs.

Fourth, the macro predictors in PCA, PLS-R y-predicted, PLS-R r-predicted FCIs' forecasting models and benchmark forecasting models are restricted to be in the same form. This is a reasonable setting because Chapter 2 has shown that FCIs have marginal predictive power compared to macro predictors. In this sense that the entry of FCIs should not affect the entry of macro predictors to a significant extent.[57] More importantly, it helps identify the predictive power of FCIs since it is difficult to disentangle the predictive power of FCIs if macro predictors are different when comparing two types of forecasting models. For example, if the domestic exchange rate is in-sample significant in the benchmark forecasting model but is replaced by the domestic export price index in the FCIs' forecasting model, the judgement that FCIs can increase their predictive power may be erroneous. This is because that the domestic export price index is likely to predict more accurately than the exchange rate in the out-of-sample period rather than that FCIs contribute extra predictive power.

Finally, in order to make the long-run equilibrium more conformable to the rationale of the world export price[58] (than that in Chapter 2), only the level world export index is allowed to one-to-one map level the import price index in the error correction (EC) term. Although the forecasting performance may be worse because of the additional restriction—one-to-one mapping in the EC term, the worsened degree may not be important. Specifically, by default, the error correction effect brought by EC terms should be increasingly significant as the forecasting term extends, namely 6-months ahead forecasting is more accurate than 1-month ahead forecasting. In this research, however, this 'longer horizon correction' effect is to a large extent offset by the imprecise prediction of the level world export price index in the out of sample period—it is predicted from its own autoregressive regression. Inevitably, the predicted value of the level world export price index drifts away from its real (*ex post*) value much further along with the increasing forecasting horizon, and, therefore, EC terms could not significantly improve the prediction in the longer forecasting horizon.

[57] From an omitted variable bias point of view, the substitutive effect or complementary effect, if there is any, should not be significant.

[58] For a closer check of the construction of the world export price, please check the previous chapter.

Experimental settings for the first hypothesis

1) Since only one long-run factor (the first factor aggregated from the single (adjusted) long-run indicator set) is used, only one short-run factor (the first factor) is allowed to be aggregated from any of the three (adjusted) short-run indicator sets—monthly, quarterly, and annual indicator sets.
2) Second, since the inappropriate estimating method (either by PCA or by PLS-R) may disturb the comparison of long-run and short-run indicators, both PCA long-run FCIs vs. PCA short-run FCIs and PLS-R y-predicted long-run FCIs vs. PLS-R y-predicted short-run FCIs are tested.[59] For example, it is possible that PCA short-run FCIs outperform PCA long-run FCIs, while PLS long-run FCIs outperform PLS short-run FCIs. Then the PCA is inappropriate owing to the rationale proceeding from (1) the in-sample weights estimated by PCA, when they are fixed for the entire out-of-sample period (fixed-weighted approach this chapter adopts), cannot have positive predictive power as those estimated by PLS-R; through (2) long-run PCA FCIs contribute more noise than short-run PCA FCIs because long-run FCIs have much slower dynamics than short-run FCIs.
3) Lastly, in addition to *ex ante* FCIs (forecasted by AR models), *ex post* FCIs are also used in order to highlight the advantage of long-run FCIs in the prediction of themselves. Because of the low frequency, the long-run FCIs can be predicted more accurately from the AR model (than the short-run FCIs). As a result, it is expected that there are more margin when comparing *ex ante* long-run FCIs with short-run FCIs than *ex post* long-run FCIs and short-run FCIs.

Experimental settings for the second hypothesis

The comparative forecasting performance test is carried out among PCA FCIs, PLS-R y-predicted and PLS-R r-predicted FCIs. In constructing the PLS-R r-predicted FCIs, the macro predictors in Step 3, the X_{macro}, are restricted to be exactly the same as those in Step 1, concerning the interpretation of PLS-R r-predicted FCIs. This is because, by definition, PLS-R r-predicted FCIs seek to explain the residual information that is not explained by macro predictors, and these macro predictors are those in Step 1 (see the end of Section 2). Therefore, if they change in Step 3, namely the final forecasting model, PLS-R r-predicted FCIs can no longer be interpreted as explaining the residual in the final forecasting model.

[59] It is in fact a two-way transmission channel. As pointed out at the beginning of Section 3, the indiscriminate usage of long-run and short-run indicators may disturb the comparison between PCA and PLS-R FCIs. Conversely, it is pointed out here that using only PCA or PLS-R weight-estimating methods may disturb the comparison between long-run and short-run indicators.

3.4 Empirical results I

This section reports empirical findings corresponding to the three hypotheses. Subsection 3.4.1 verifies the first hypothesis by showing that both PCA and PLS-R y-predicted FCIs, constructed from (adjusted) long-run indicator sets, have better predictive power than those from (adjusted) short-run indicator sets. Subsection 3.4.2 partly verifies the second hypothesis by showing that in general PLS-R r-predicted that FCIs outperform PLS-R y-predicted FCIs, while the latter outperform PCA FCIs regarding three target economies, namely Singapore, Korea, and Taiwan. Focusing on the PLS-R FCIs only, Subsection 3.4.3 first verifies the third hypothesis by showing that in general the predictive power of FCIs reach their highest at the first subsample, then fall sharply at the second subsample, and then are moderately regained at the third subsample; Subsection 3.4.3 then explains the forecasting failure of PLS-R FCIs, that is, the failure of the second hypothesis, from a subsample point of view.

3.4.1 Comparison among long-run FCIs, short-run FCIs, and the benchmark forecasting model

From Table 3.2 and Table 3.3, this subsection finds that FCIs constructed from short-run indicators (henceforth, short-run FCIs) are inferior to FCIs constructed from long-run indicators (henceforth, long-run FCIs) and the benchmark model.

Before a closer investigation in Table 3.2 and Table 3.3, there is an important finding in Table 3.1: the same two counter-intuitive model specifications occur to PCA FCIs as occur to DFM FCIs, while the specification of the PLS-R FCIs' forecasting model is more conformable to common sense. The common sense on the specification of FCIs is: both short-run and long-run indicators should be included in the final forecasting model in short-lagged form, and they should also be included in the final forecasting model in the level form rather in the differenced form. PCA FCIs violate the common sense in that (1) at least 4-month lagged short-run FCIs are in-sample significant in the final FCIs' forecasting model regarding Thailand, Indonesia, and Malaysia; and (2) long-run FCIs in the differenced form are in-sample significant in the final FCIs' forecasting model regarding Singapore, Thailand, Indonesia, and Malaysia. By contrast, 1-month lagged PLS-R FCIs, both short-run and long-run FCIs, are overwhelmingly in-sample significant regarding all six target economies. I shall come back to the implication of this finding (regarding the forecasting performance of PCA FCIs vs. PLS-R FCIs) later in the following Subsection 3.4.2 and move on to the forecasting performance of long-run FCIs vs. short-run FCIs now.

An introduction of the structure of Table 3.2 and Table 3.3 is necessary because they are multi-dimensionally constructed. In general, Table 3.2 and Table 3.3 are constructed with two blocks. The upper block reports the forecasting performance of short-run FCIs vs. the benchmark forecasting model in order to show that short-run FCIs contribute more of noise than signal to the forecasting; the lower block reports the forecasting performance of long-run FCIs vs. the short-run FCIs' forecasting models. Then in each block, there are two columns listed for each target economy. The left column reports the forecasting performance of *ex post* FCIs while the right column reports that of *ex ante* FCIs and the reason for doing this is discussed in Subsection 3.2.1. Finally each cell reports the ratio of rooted mean squared forecasting error (henceforth, RRMSFE) and the p-value of MDM statistics (see Chapter 2) to test the comparative forecasting performance.

The RRMSFE statistics and its p-value verify the first hypothesis. That is, the lower block of Table 3.2 and Table 3.3 show that both PCA and PLS-R (y-predicted) short-run FCIs are inferior to their long-run FCIs. The last issues discussed in Subsection 3.2.2 are also clarified in that the margin of predictive power of *ex ante* long-run FCIs vs. *ex ante* short-run FCIs is larger than that of *ex post* long-run FCIs vs. *ex post* short-run FCIs. Taking Singapore as an example, in the lower block of Table 3.2, the p-value of 6-month ahead *ex post* long-run FCIs vs. *ex post* short-run FCIs is 0.439, namely weak power to support the first hypothesis. By contrast, the p-value of 6-month ahead *ex ante* long-run FCIs vs. *ex ante* short-run FCIs is 0.996, namely strong power to support the first hypothesis.

The upper block of Table 3.2 and Table 3.3 shows that both PCA and PLS-R short-run FCIs' forecasting models are inferior to benchmark models regarding all of the six target economies. Therefore, in the following analysis, PCA FCIs and PLS-R FCIs are exclusively constructed from long-run indicators.

3.4.2 PLS-R r-predicted FCIs vs. PLS-R y-predicted FCIs vs. PCA vs. the Benchmark model

From Table 3.4, this subsection partly verifies the second hypothesis with respect to Singapore, Korea, and Taiwan, while it fails for Indonesia and Malaysia. Table 3.5 is a summary of Table 3.4. From it, the six target economies can be divided into four groups: (1) with respect to Singapore, Korea, and Taiwan, both PLS-R y-predicted and PLS-R r-predicted FCIs outperform PCA

FCIs[61]; (2) for Thailand, the same result is found but with a weak statistical power judging by the p-value of MDM statistics; (3) for Indonesia, the PLS-R y-predicted FCIs' forecasting model is inferior to both the PCA and benchmark models, while the PLS-R r-predicted FCIs' forecasting model is superior to both PLS-R y-predicted FCIs and PCA FCIs forecasting models; (4) for Malaysia, the PLS-R FCIs' forecasting model is inferior to both the PCA FCIs and benchmark forecasting models.

The forecasting failure of the PLS-R FCIs' forecasting model with respect to Indonesia and Malaysia can be explained by the location shift (see Chapter 2). According to Hendry and Doornik (1997); Hendry and Clements (2003); and Hendry and Clements (2004), a significant location shift—if not corrected in time—will cause significant forecasting failure. From Table 3.1, PCA FCIs are included in the final forecasting model in the differenced form, while PLS-R FCIs are included in the final forecasting model in the level form.[62] If a location shift was present during the 2008 crisis, which is quite likely, the level PLS-R FCIs will contribute much more noise than the differenced PCA FCIs because the location shift is largely differenced out for the differenced PCA FCIs.[63] In fact, the following Subsection 3.4.3 will show that the PLS-R FCIs in the level form contribute significant noise than differenced PCA FCIs post-2008 crisis.

3.4.3 Subsample out-of-sample encompassing tests

This subsection verifies the third hypothesis reported in Table 3.7. Specifically, all six target economies saw the predictive power their FCIs, the PCA FCIs, PLS-R y-predicted FCIs and PLS-R r-predicted FCIs, disappear to a significant extent during the 2008 crisis (07M5–09M6) after reaching a high level pre-2008 crisis (07M5–08M9).

Only two exceptional cases are found. With respect to Korea and Taiwan, PLS-R r-predicted FCIs' outperform the benchmark model in all three subsamples. They are not exceptional to the extent that they can save the forecasting model from a collapse during the 2008 crisis. Figure 3.2 describes 3-months leading RMSFE of the PLS-R r-predicted FCIs' and the benchmark forecasting model with respect to all three subsamples and the whole out-of-sample period. All the six economies, except Malaysia, see the surging forecasting error during the 2008 crisis

[61] And since PCA FCIs outperform the benchmark model, PLS-R FCIs can improve the forecasting accuracy more significantly over the benchmark model

[62] That is, it corresponds to the important finding in Section 4.1 (last Subsection).

[63] I shall first elaborate this point in Chapter 5 as 'a second postulation'.

(2007M5–2008M9).[64] Even the PLS-R r-predicted FCIs cannot save forecasting models from a collapse during the 2008 crisis.

The postulation proposed at the end of Subsection 3.4.2 can be verified. Regarding Indonesia and Malaysia, the difference in the surviving form between PCA FCIs and PLS-R FCIs should be responsible for the inferior forecasting performance of PLS-R FCIs, rather than the difference in the estimating method. Table 3.1[65] shows that: (1) for Indonesia, the two types of PLS-R FCIs survived in the level form, outperformjng PCA FCIs in the differenced form pre-2008 crisis but are inferior to PCA FCIs during 2008 crisis; (2) for Malaysia, the PLS-R r-predicted FCIs in the level form outperform both PLS-R y-predicted FCIs and PCA FCIs in the differenced form pre-2008 crisis but the level PLS-R r-predicted FCIs gradually lose their superiority post-2008 crisis until the worst case that they are significantly inferior to the differenced PLS-R y-predicted FCIs and PCA FCIs.

3.5 Empirical results II

Since the superiority of PLS-R FCIs, compared to PCA FCIs, are empirically supported in Section 3.4, this section shall further decompose the PLS-R FCIs—both PLS-R y-predicted and PLS-R r-predicted FCIs—and analyses the disaggregate contribution to the prediction of each financial indicator through the corresponding weight estimates. Because, by construction, (1) PLS-R FCIs, both PLS-R y-predicted and PLS-R r-predicted FCIs, take account of the correlation between the target variable and the financial indicator matrix; and furthermore, (2) when a different target variable is used regarding different target economies, weight estimates could be quite different between PLS-R y-predicted FCIs and PLS-R r-predicted FCIs, and different regarding different target economies. In this sense, the following disaggregated analysis is divided into different groups according to both different target economies and the different types of PLS-R FCIs.

As the following analysis will show through Table 3.14, communality among the six target economies is found (and will not be repeated in the following analysis of individual economies):

- Weight estimates of bond–equity yield ratios and equity–commodity price ratios are small;

[64] It is because Malaysia's forecasting model is from an AR(2) model, which strongly signals FCIs are quite unlikely to contribute a predictive power for a long time because the major explanatory macro predictors drop out in the forecasting model.
[65] There is no strong statistical power showing that is more superior in between PLS-R FCIs and PCA FCIs in three subsample analyses.

- Weight estimates of the TED spread, money–inflation rate ratios, and money–bond interest ratios are very large.

Among the indicators with weight estimates varying significantly across the six target economies, regularity is also found.

- Weight estimates of derivative indicators are large in regard to the three developed economies—Singapore, Korea, and Taiwan.
- Weight estimates of UK and US indicators are always significant regarding the three developed economies, while it is the weight estimates of Japanese indicators that dominate (overwhelmingly large) in regard to the remaining three less developed economies. These unique features conversely highlight that FCIs estimated by PCA are unlikely to apply to largely different economies.
- The comparison between weight estimates for PLS-R y-predicted FCIs and PLS-R r-predicted FCIs shows that by purging the effect of macro predictors, the effect of some financial indicators are also purged. This can be a serious issue since the weight estimates of derivative indicators, which are significant for PLS-R y-predicted FCIs, become insignificant for PLS-R r-predicted FCIs with respect to Singapore and Korea.

Disaggregated contribution of financial indicators for each individual target economy is reported next.

Singapore

- Concerning the PLS-R y-predicted FCIs, weight estimates of derivative indicators are significant (larger than 0.2). Geographically, among 10 indicators with insignificant weight estimates (smaller than 0.05), 4 are UK indicators (from the UK financial market); among 10 indicators with significant weight, 5 are also UK indicators.
- Concerning the PLS-R r-predicted FCIs, weight estimates of the banking sector indicators are significant, yet the weight estimates of the derivative indicators are less significant. Geographically, 2 out of 4 insignificant indicators are Japanese indicators while 4 out of 9 significant indicators are US indicators.

It therefore seems that, by purging the predictive power of macro predictors, the predictive power of the derivative market is purged, while the banking sector plays a more important role, and the predictive power of UK indicators is replaced by that of US indicators.

Korea

- Concerning PLS-R y-predicted FCIs, weight estimates of the derivative indicators are significant. Geographically, insignificant indicators are dominated by Japan's indicators (4/6), and significant indicators are dominated by UK indicators (4/10).
- Concerning PLS-R r-predicted FCIs, weight estimates of equity–commodity price ratios are significant. Geographically, insignificant indicators are dominated by UK indicators (5/10), and significant indicators are also dominated by UK indicators (5/10).

It therefore seems that, by purging the predictive power of macro predictors, the predictive power of derivative indicators is purged also.

Taiwan

- Concerning PLS-R y-predicted FCIs, weight estimates of the derivative indicators are significant.
- Concerning PLS-R r-predicted FCIs, weight estimates of yield structures of money market interest rate become insignificant.

No significant geographical shift is observed, when the predictive power of macro predictors is purged.

Thailand

- Concerning PLS-R y-predicted FCIs, insignificant indicators are dominated by US indicators (7/12), and significant indicators are dominated by UK indicators (4/9).
- Concerning PLS-R r-predicted FCIs, weight estimates of covered interest parity indicators are significant. Geographically, insignificant indicators are dominated by UK indicators (4/9), and significant indicators are dominated equally by UK and Japanese indicators (4/10 each).

It therefore seems that, by purging the predictive power of macro predictors, the Cover Interest Parity contribute a higher significant weight to the prediction at the aggregate level.

Indonesia

- Concerning PLS-R y-predicted FCIs, weight estimates concentrate on several Japanese indicators measuring yield structures of money market, TED spread, and yield structures of bond market and money–inflation rate ratios. As a result, indicators of money-bond interest ratios have surprisingly insignificant weight estimates, and covered interest parity indicators also have insignificant weight estimates.

- Concerning PLS-R r-predicted FCIs, weight estimates of indicators are less concentrated, but most of them are still Japanese indicators (5/10). Money–bond interest ratios are back to normal, namely their weight estimates are significant (similar to other target economies).

It therefore seems that, by purging the predictive power of macro predictors, money–bond interest ratios are purged.

Malaysia

- Concerning PLS-R y-predicted FCIs, the indicator of TED spread from Japan dominates with weight reaching 0.6, compared to the second largest one reaching only half of it, namely 0.3. Also, the derivative indicators have considerable small weights, especially compared to the above five economies.
- Concerning PLS-R r-predicted FCIs, weights are more evenly distributed across different indicators. Unlike the other five economies, housing–equity price ratios are found to have a significant weight estimate.

It therefore seems that, by purging the predictive power of macro predictors, TED spread is purged.

3.6 Conclusion

This chapter adopts PLS-R to estimate FCIs. Because of the similar dynamics between PCA FCIs and DFM FCIs, several results found in this chapter can be directly compared to those in last chapter when PLS-R FCIs was compared to PCA FCIs.

- Chapter 2 only confirmed the superiority of separated FCIs against mixed FCIs, but both types of FCIs are aggregated from long-run and short-run financial indicators. This chapter moves one step further by separating long-run FCIs from short-run FCIs in constructing the final FCIs' forecasting models and empirically finds that long-run FCIs have better forecasting power than short-run FCIs, a finding consistent with QH's argument.
- The evidence on the superiority of long-run FCIs against short-run FCIs is further enhanced by the experiment on *ex ante* FCIs vs. *ex post* FCIs. It was postulated in Chapter 2 that long-run FCIs have a further advantage over short-run FCIs, in that they can be more effectively forecast out-of-sample. This chapter verifies the postulation by showing that, in terms of improvement to forecasting, the margin of *ex ante* long-run FCIs

over *ex ante* short-run FCIs is larger than that of *ex post* long-run FCIs over *ex post* short-run FCIs.

- The two counter-intuitive specifications of PCA-DFM FCIs are not found in PLS FCIs. It is primarily postulated here that since PLS FCIs contain more predictive information and less noisy information, it is less probable that model misspecification, in terms of FCIs, will be present.
- PLS-R r-predicted FCIs can consistently outperform the benchmark model across all six target economies through a subsample predictive test—07M5–08M9, while PCA FCIs fail in the cases of Thailand and Malaysia (consistent with the forecasting performance of DFM FCIs in last chapter).
- Chapter 2 discussed the location shift issue for disaggregated financial indicators, in the sense that FCIs aggregated from long-run indicators are more likely to experience location shift out-of-sample than those aggregated from short-run indicators. This chapter also discusses the location shift issue but with respect to the surviving form in the final FCIs' forecasting models. Specifically, although PLS-R FCIs are frequently in-sample significant in the level form, they are more likely to experience location shift out-of-sample than those of PCA-DFM FCIs that have survived in the differenced form. It is the same reason, as offered in Chapter 2, for this phenomenon: location shift occurring with aggregate FCIs is differenced out in PCA-DFM FCIs' forecasting models.

Based on subsample predictive tests, this chapter also finds that FCIs, estimated either by PCA or PLS-R, turn into significant noise during the 2008 crisis. This finding corroborates those of Aramonte et al. (2013) and Koop and Korobilis (2014), in the sense that *ex ante* FCIs lost their predictive power during the 2008 crisis, although *ex post* FCIs may have maintained predictive power during the 2008 crisis.

In addition to the findings with respect to the aggregate FCIs, this chapter also investigates the predictive power at the indicator level through an experimental design based on fixed weights for the entire out-of-sample period. The important findings are restated as follows.

- First and most importantly, weight estimates are quite different across different target economies, and the differences reflect characteristics of the different target economies to a certain extent. For example, weight estimates of derivative indicators are large with respect to the three developed economies with a high degrees of openness for their financial sectors—Singapore, Korea, and Taiwan, while they are relatively much smaller with respect to the remaining three developing economies that have lower degrees of openness for their financial sectors.[71] Since the derivative indicators are diversified products in the forms of futures and options markets that can cover a large range of underlying macro economies, they should provide for more accurate prediction, with respect to the three developed economies with high degrees of openness for their financial sectors, but less so with respect to the three developing economies with a lower degrees of openness for their financial sectors.

- Second, weight estimates of the external TED spread, money–inflation rate ratios and money-bond interest ratios are large regarding all six target economies. Since short-term interest rate variables are used to construct all these three types of long-run indicators (see Table 3.1), it is postulated here that external interest rates contains rich predictive information.
- Third, weight estimates of bond–equity yield ratios and equity–commodity price ratios are small regarding all six target economies. The trivial pass through from cross-equity international markets to the six domestic markets corroborates the equity home bias argued by French and Poterba (1991); and Tesar and Werner (1995). These two studies found empirically that investors only hold modest amount of foreign equity.
- Lastly, although PLS-R r-predicted FCIs have better forecasting power than PLS-R y-predicted FCIs, especially with respect to the three economies with more open financial sectors, the disaggregated analysis raises questions about PLS-R r-predicted FCIs. For example, In the process of purging the predictive power of macro predictors,[72] derivative indicators for PLS-R r-predicted FCIs, which contain important predictive information, are also purged.

In summary, from the predictive tests on the aggregate FCIs, this chapter finds that the PLS-R FCIs' forecasting models have a better forecasting performance than PCA FCIs' forecasting models; the disaggregated analysis of PLS-R FCIs, in particular, finds that derivative indicators have relatively large weight estimates, with respect to the three financially open economies, but small weights with respect to the three less open economies.

[71] See Chapter 1 for the economic background information of the six target economies.
[72] Please refer to the construction of PLS-R r-predicted FCIs in Subsection 3.2.2.

Appendix 3A: Iterative least squares to estimate PLS and PCA factors

For PCA, the following sequential iterative least squares algorithm illustrates how to minimize u and get a useful relation within X.

1) Take any vector x_i from X and call it t_i;
2) $\widehat{W}_1^T = t_i^{\mathrm{T}}\mathrm{X}$, X is the financial indicator matrix, Y is the import price index, and W is the primary weight vector to estimate first PLS factor
3) $\widehat{\mathrm{W}}_{1,\mathrm{norm}}^{\mathrm{T}} = \widehat{W}_1^T / \|\widehat{W}_1\|$, normalization of the primary weight estimates
4) $\widehat{\mathrm{F}}_1 = \mathrm{X}\widehat{\mathrm{W}}_{1,\mathrm{norm}}$, $\widehat{\mathrm{F}}_1$ is the first PCA factor
5) Step 1)–3) is repeated but X is replaced by $\widehat{\mathrm{X}} = X - X\widehat{F}_1 \left(\widehat{F}_1^T\widehat{F}_1\right)^{-1}\widehat{F}_1^T X$, which is a matrix with its column vector corresponding to the OLS residual vector of financial indicator (the column vector of financial indicator matrix X) regressed on $\widehat{\mathrm{F}}_1$, and Y is replaced by $\widehat{Y} = Y - \left(\widehat{F}_1^T\widehat{F}_1\right)^{-1}\widehat{F}_1^T Y$, which is the OLS residual vector of Y regressed on $\widehat{\mathrm{F}}_1$

For PLS, the following sequential iterative least squares algorithm illustrates how to minimize u and get a useful relation between X and y.

1) $\widehat{W}_1^T = \mathrm{Y}^{\mathrm{T}}\mathrm{X}$, X is the financial indicator matrix, Y is the import price index, and W is the primary weight vector to estimate first PLS factor
2) $\widehat{\mathrm{W}}_{1,\mathrm{norm}}^{\mathrm{T}} = \widehat{W}_1^T / \|\widehat{W}_1\|$, normalization of the primary weight estimates
3) $\widehat{\mathrm{F}}_1 = \mathrm{X}\widehat{\mathrm{W}}_{1,\mathrm{norm}}$, $\widehat{\mathrm{F}}_1$ is the first PLS factor
4) Step 1)–-3) is repeated, but X is replaced by $\widehat{\mathrm{X}} = X - X\widehat{F}_1 \left(\widehat{F}_1^T\widehat{F}_1\right)^{-1}\widehat{F}_1^T X$, which is a matrix with its column vector corresponding to the OLS residual vector of financial indicator (the column vector of financial indicator matrix X) regressed on $\widehat{\mathrm{F}}_1$, and Y is replaced by $\widehat{Y} = Y - \left(\widehat{F}_1^T\widehat{F}_1\right)^{-1}\widehat{F}_1^T Y$, which is the OLS residual vector of Y regressed on $\widehat{\mathrm{F}}_1$

Appendix 3B: Newly added financial variables and indicators

1. Newly added financial variables

Name	Description	Source
R_10YBrate_UK	UK: 10 Y Zero Coupon rate	CEIC
R_5YBrate_UK	UK: 5 Y Zero Coupon rate	CEIC
R_OROF_US	Open Interest: Financial Options	CEIC
R_ORO_JP	OSE: Open Interest: Nikkei 225 Options	CEIC
R_ORF_JP	OSE: Open Interest: Nikkei 225 Futures	CEIC
R_IssL_JP	JP: volume: long term Government Bonds	CEIC
R_IssM_JP	JP: volume: medium term Government Bonds	CEIC
R_ComPaperOT_US	US: Total Commercial Paper Outstanding	CEIC
R_CompaperOF_US	US: Commercial Paper Outstanding: Financial	CEIC
R_ComBLoanT_US	US: Commercial Banks: Interbank Loans	CEIC
R_ComBloanF_US	US: Commercial Banks: Interbank Loans: Commercial	CEIC

2. Adjusted long-run financial indictors

Market misalignment types (Name)	Indicator Name	ID	Transformation to be stationary[73]	Variable name and Data Source[74]			
Bond market vs. Equity market (BE)	BE_R_JP (N.I.)	x1	1 - 2	R_BRate_JP		R_EquityYield_JP	
	BE_R_UK	x2	1 - 2	R_BRate_UK		R_ EquityYield _UK	
	BE_R_US	x3	1 – 2	R_BRate_US		R_ EquityYield _US	
Money market vs. Forex market (CIP)	CIP_JP	x4	(1 - 2) - (ln(3) – ln(4))	R_MRate_JP	R_MRate_US	R_ERF_JP	R_ER_JP
	CIP_UK	x5	(1 - 2) - (ln(3) – ln(4))	R_MRate_UK	R_MRate_US	R_ERF_UK	R_ER_UK
Equity market vs. Commodity market (ECPI)	ECPI_R_JP (N.I.)	x6	1 / 2	R_EP_JP		R_CPI_JP	
	ECPI_R_UK	x7	1 / 2	R_EP_UK		R_CPI_UK	
	ECPI_R_US	x8	1 / 2	R_EP_US		R_CPI_US	

[73] Calculation of stationary indicator from financial variables listed to its right column. The number in each cell denotes the column number. For example, the calculation of BE_R_UK is R_Brate_UK-R_Brate_UK, namely the 1st column minus the 2nd column to its right.

[74] Since DH list the data source in detail and this research basically uses the same financial variables, the data source in detail is not listed. For a detailed data source, please refer to QH's Appendix (Qin and He 2012, 28–29).

Bond market: Yield structures (GOV)	Gov_SP_DE	x9	1 - 2	R_Brate_DE	R_Trate_DE
	Gov_SP_JP	x10	1 - 2	R_Brate_JP	R_Trate_JP
	Gov_SP_UK	x11	1 - 2	R_Brate_UK	R_Trate_UK
	GOV_SP_UK1 (N.I.)	x12	1 - 2	R_10YBrate_UK	R_5YBrate_UK
	Gov_SP_US	x13	1 - 2	R_Brate_US	R_Brate_US
	GOV_Q_JP (N.I.)	x14	1 / 2	R_IssL_JP	R_IssM_JP
Money market: Yield structures (Mrate)	MRate_SP_JP	x15	1 - 2	R_libor_JP	R_Mrate_JP
	MRate_SP_UK	x16	1 - 2	R_libor_UK	R_Mrate_UK
Equity market	S&P_R_US	x17	1 / 2	R_S&PF_US	R_S&P_US
TED spread	TED_SP_JP (N.I.)	x18	1 - 2	R_Mrate_JP	R_Trate_JP
	TED_SP_UK	x19	1 - 2	R_Mrate_UK	R_Trate_UK
	TED_SP_US	x20	1 - 2	R_Mrate_US	R_Trate_US
Forex market	ERFER_SP_UK	x21	1 - 2	R_ERF_UK	R_ER_UK
Money market vs. Bond market (MB)	MB_R_EU (N.I.)	x22	1 / 2	R_Mrate_EU	R_Brate_EU
	MB_R_JP (N.I.)	x23	1 / 2	R_Mrate_JP	R_Brate_JP
	MB_R_UK (N.I.)	x24	1 / 2	R_Mrate_UK	R_Brate_UK
	MB_R_US (N.I.)	x25	1 / 2	R_Mrate_US	R_Brate_US
Derivative Market (Deriv)	FuOption_US (N.I.)	x26	1 / 2	R_ORFF_US	R_OROF_US
	FuOption_R_JP (N.I.)	x27	1 / 2	R_ORF_JP	R_ORO_JP
Money market vs. Commodity market (RRate)	RRate_3m_UK	x28	1 / g(2)[75]	R_Mrate_JP	R_CPI_UK
	RRate_3m_US	x29	1 / g(2)	R_Mrate_JP	R_CPI_UK
	RRate_3m_JP (N.I.)	x30	1 / g(2)	R_Mrate_JP	R_CPI_UK
Real estate market vs. Equity market (HPEP)	HPEP_R_UK (N.I.)	x31	1 / 2	R_HP_JP	R_EP_JP
	HPEP_R_US (N.I.)	x32	1 / 2	R_HP_US	R_EP_US
Money market: Quantity	ComPaperF_R_US (N.I.)	x33	1 / 2	R_CompaperOF_US	R_ComPaperOT_US
Banking sector	ComBLoanF_R_US (N.I.)	x34	1 / 2	R_ComBloanF_US	R_ComBLoanT_US
	LD_R_US	x3	1 / 2	R_Loan_US	R_Deposit_US

[75]The term ‘g( )’ denotes growth rate transformation

3. Adjusted short-run indicators

Indicator name	Variable name
Brate_EU	Δ(R_BRate_EU)
Brate_FR	Δ(R_BRate_FR)
BRate_JP	Δ(R_BRate_JP)
BRate_UK	Δ(R_BRate_UK)
BRate_US	Δ(R_BRate_US)
coupon10_UK	g(R_0coupon10_UK)
coupon5_UK	g(R_0coupon5_UK)
MRATE_EU	Δ(R_MRate_EU)
MRATE_JP	Δ(R_MRate_JP)
MRATE_UK	Δ(R_MRate_UK)
Mrate_US	Δ(R_MRate_US)
ER_JP	g(R_ER_JP)
ER_UK	g(R_ER_UK)
Comp	g(R_Comp)
EMF_US	g(R_EMF_US)
EP_JP	g(R_EP_JP)
EP_UK	g(R_EP_UK)
EP_US	g(R_EP_US)
BarclaysGB	g(R_BarclayGB)
LOAN_JP	Δ(R_Loan_JP-g(R_CPI_JP))
LOAN_UK	Δ(R_Loan_UK-g(R_CPI_UK))
LOAN_US	Δ(R_Loan_US-g(R_CPI_US))
M1_JP	Δ(R_M1_JP-g(R_CPI_JP))
M1_UK	Δ(R_M1_UK-g(R_CPI_UK))
M1_US	Δ(R_M1_US-g(R_CPI_US))
IssL_JP	g(IssL_JP)
ORFF_US	g(R_ORF_US)
OROF_US	Δ(R_OROF_US)
ORO_JP	g(R_ORO_JP)
ORF_JP	g(R_ORF_JP)
SPT_US	g(R_S&PT_US)
TSENoSE1_JP	g(R_TSE_JP)
ForexSwap_JP	g(R_ERF_JP)
ComBLoanT_US	g(ComBankLoan_US)
HP_UK	g(R_HP_UK)
HP_US	g(R_HP_US)
ComPaperOT_US	g(ComPaperOT_US)

Appendix 3C: Specification of benchmark, PCA, PLS-R y-predicted, and r-predicted FCIs' forecasting models

1. Singapore

$$\Delta SG_t = 0.17\Delta SG_{t-1} - 0.069\Delta SG_{t-2} + 0.55\Delta SG_{dp,t} - 0.38\Delta SG_{er,t} - 0.027(SG - SG_{wp})_{t-1} + \varepsilon_t$$

(0.033)	(0.031)	(0.041)	(0.048)	(0.0099)	(0.0065)
(0.08)	(0.035)	(0.47)	(0.24)	(0.020)	
(0.15)	(0.39)	(0.144)	(0.069)	(0.036)	(1.12)

$$\Delta SG_t = 0.16\Delta SG_{t-1} - 0.071\Delta SG_{t-2} + 0.55\Delta SG_{dp,t} - 0.38\Delta SG_{er,t} - 0.028(SG - SG_{wp})_{t-1} - 0.00030\,{}^{pca}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.032)	(0.032)	(0.041)	(0.049)	(0.001)	(0.00014)	(0.0064)
(0.13)	(0.027)	(0.48)	(0.24)	(0.040)	(0.024)	
(0.16)	(0.34)	(0.027)	(0.085)	(0.067)	(0.093)	(1.20)

$$\Delta SG_t = 0.16\Delta SG_{t-1} - 0.082\Delta SG_{t-2} + 0.54\Delta SG_{dp,t} - 0.37\Delta SG_{er,t} - 0.036(SG - SG_{wp})_{t-1} + 0.00048\,{}^{pls}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.032)	(0.031)	(0.041)	(0.049)	(0.010)	(0.00019)	(0.0064)
(0.11)	(0.03)	(0.48)	(0.24)	(0.06)	(0.03)	
(0.16)	(0.033)	(0.067)	(0.033)	(0.030)	(0.037)	(1.02)

$$\Delta SG_t = 0.15\Delta SG_{t-1} - 0.064\Delta SG_{t-2} + 0.55\Delta SG_{dp,t} - 0.38\Delta SG_{er,t} - 0.034(SG - SG_{wp})_{t-1} + 0.00031\,{}^{pls}_{resid}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.034)	(0.033)	(0.042)	(0.049)	(0.010)	(0.00016)	(0.0065)
(0.10)	(0.02)	(0.48)	(0.25)	(0.055)	(0.02)	
(0.16)	(0.26)	(0.064)	(0.035)	(0.075)	(0.080)	(0.86)

2. Korea

$$\Delta KOR_t = 0.42\Delta KOR_{wp,t} + 0.17\Delta KOR_{wp,t-1} + 0.73\Delta KOR_{dp,t} - 0.047\Delta\Delta KOR_{er,t-3} - 0.012(KOR - KOR_{wp})_{t-1} + \varepsilon_t$$

(0.059)	(0.058)	(0.070)	(0.021)	(0.0047)	(0.010)
(0.21)	(0.044)	(0.37)	(0.027)	(0.033)	
(2.35*)	(0.071)	(0.42)	(0.030)	(0.24)	(3.18*)

$$\Delta KOR_t = 0.41\Delta KOR_{wp,t} + 0.15\Delta KOR_{wp,t-1} + 0.73\Delta KOR_{dp,t} - 0.046\Delta\Delta KOR_{er,t-3} - 0.014\left(KOR - KOR_{wp}\right)_{t-1} - 0.00064\,{}^{pca}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.058)	(0.057)	(0.068)	(0.020)	(0.0047)	(0.00022)	(0.0099)
(0.21)	(0.038)	(0.38)	(0.027)	(0.047)	(0.043)	
(2.07*)	(0.12)	(0.37)	(0.031)	(0.19)	(0.18)	(2.94*)

$$\Delta KOR_t = 0.40\Delta KOR_{wp,t} + 0.15\Delta KOR_{wp,t-1} + 0.70\Delta KOR_{dp,t} - 0.046\Delta\Delta KOR_{er,t-3} - 0.014\left(KOR - KOR_{wp}\right)_{t-1} - 0.00069\,{}^{pls}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.059)	(0.058)	(0.070)	(0.020)	(0.0047)	(0.00027)	(0.010)
(0.20)	(0.036)	(0.35)	(0.027)	(0.044)	(0.032)	
(2.18*)	(0.10)	(0.40)	(0.029)	(0.14)	(0.18	(3.15*)

$$\Delta KOR_t = 0.41\Delta KOR_{wp,t} + 0.16\Delta KOR_{wp,t-1} + 0.76\Delta KOR_{dp,t} - 0.046\Delta\Delta KOR_{er,t-3} - 0.016\left(KOR - KOR_{wp}\right)_{t-1} - 0.00088\,{}^{pls}_{resid}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.057)	(0.056)	(0.067)	(0.020)	(0.0047)	(0.00023)	(0.098)
(0.20)	(0.039)	(0.41)	(0.028)	(0.059)	(0.075)	
(1.95*)	(0.13)	(0.35)	(0.034)	(0.27)	(0.40)	(3.46*)

3. Taiwan

$$\Delta TW_t = 0.19\Delta TW_{t-1} + 0.38\Delta TW_{wp,t} + 0.80\Delta TW_{dp,t} - 0.21\Delta TW_{dp,t-4} - 0.1\Delta TW_{er,t-3} - 0.016(TW - TW_{wp})_{t-1} + \varepsilon_t$$

(0.057)	(0.055)	(0.11)	(0.099)	(0.045)	(0.008)	(0.008)
(0.059)	(0.21)	(0.22)	(0.025)	(0.027)	(0.021)	
(0.034)	(0.24)	(0.053)	(0.047)	(0.18)	(0.042)	(0.84)

$$\Delta TW_t = 0.19\Delta TW_{t-1} + 0.38\Delta TW_{wp,t} + 0.80\Delta TW_{dp,t} - 0.21\Delta TW_{dp,t-4} - 0.1\Delta TW_{er,t-3} - 0.016\left(TW - TW_{wp}\right)_{t-1} - 0.00043\,{}^{pca}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.057)	(0.055)	(0.11)	(0.097)	(0.044)	(0.008)	(0.0018)	(0.0080)
(0.046)	(0.21)	(0.24)	(0.022)	(0.028)	(0.022)	(0.032)	
(0.068)	(0.16)	(0.036)	(0.082)	(0.17)	(0.094)	(0.39)	(1.32)

$$\Delta TW_t = 0.15\Delta TW_{t-1} + 0.38\Delta TW_{wp,t} + 0.78\Delta TW_{dp,t} - 0.23\Delta TW_{dp,t-4} - 0.098\Delta TW_{er,t-3} - 0.019\left(TW - TW_{wp}\right)_{t-1} + 0.00069\,{}^{pls}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.057)	(0.054)	(0.11)	(0.097)	(0.044)	(0.008)	(0.0023)	(0.0079)
(0.038)	(0.21)	(0.22)	(0.029)	(0.026)	(0.029)	(0.046)	
(0.057)	(0.20)	(0.056)	(0.061)	(0.17)	(0.090)	(0.59)	(0.98)

$$\Delta TW_t = 0.16\Delta TW_{t-1} + 0.39\Delta TW_{wp,t} + 0.81\Delta TW_{dp,t} - 0.21\Delta TW_{dp,t-4} - 0.10\Delta TW_{er,t-3} - 0.019\left(TW - TW_{wp}\right)_{t-1} + 0.00062\,{}^{pls}_{resid}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.057)	(0.054)	(0.11)	(0.097)	(0.044)	(0.008)	(0.0020)	(0.0079)
(0.038)	(0.21)	(0.22)	(0.029)	(0.026)	(0.029)	(0.046)	
(0.098)	(0.13)	(0.040)	(0.078)	(0.16)	(0.12)	(0.11)	(1.01)

4. Thailand

$$\Delta TH_t = -0.36\Delta TH_{t-1} + 0.21\Delta TH_{t-2} + 0.27\Delta TH_{wp,t} + 0.33\Delta TH_{dp,t} + \varepsilon_t$$

(0.067)	(0.068)	(0.083)	(0.11)	(0.015)
(0.13)	(0.046)	(0.053)	(0.048)	
(0.074)	(0.015)	(0.36)	(0.16)	(1.86)*

$$\Delta TH_t = -0.36\Delta TH_{t-1} + 0.20\Delta TH_{t-2} + 0.25\Delta TH_{wp,t} + 0.37\Delta TH_{dp,t} + 0.0080\Delta\,{}^{pca}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.067)	(0.068)	(0.083)	(0.11)	(0.0038)	(0.015)
(0.13)	(0.045)	(0.047)	(0.058)	(0.02)	
(0.066)	(0.015)	(0.32)	(0.19)	(0.071)	(1.88)*

$$\Delta TH_t = -0.40\Delta TH_{t-1} + 0.17\Delta TH_{t-2} + 0.25\Delta TH_{wp,t} + 0.30\Delta TH_{dp,t} + 0.0011\,{}^{pls}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.069)	(0.069)	(0.083)	(0.11)	(0.00053)	(0.015)
(0.15)	(0.031)	(0.048)	(0.040)	(0.026)	
(0.077)	(0.015)	(0.41)	(0.21)	(0.10)	(2.43)*

$$\Delta TH_t = -0.40\Delta TH_{t-1} + 0.16\Delta TH_{t-2} + 0.28\Delta TH_{wp,t} + 0.35\Delta TH_{dp,t} + 0.0014\,{}^{pls}_{resid}f^{1}_{lr,t-1} + \varepsilon_t$$

(0.068)	(0.068)	(0.082)	(0.11)	(0.00052)	(0.015)
(0.15)	(0.030)	(0.06)	(0.054)	(0.038)	
(0.088)	(0.018)	(0.37)	(0.13)	(0.26)	(2.97)*

5. Indonesia

$$\Delta ID_t = 0.51\Delta ID_{dp,t} - 0.53\Delta ID_{er,t} + \varepsilon_t$$

(0.037)	(0.026)	(0.016)
(0.64)	(0.79)	
(0.15)	(0.016)	(1.52**)

$$\Delta ID_t = 0.50\Delta ID_{dp,t} - 0.53\Delta ID_{er,t} - 0.0077\Delta_3{}^{pca}f^1_{lr,t-2} + \varepsilon_t$$

(0.036)	(0.026)	(0.0033)	(0.015)
(0.64)	(0.80)	(0.046)	
(0.142)	(0.017)	(0.26)	(1.57*)

$$\Delta ID_t = 0.49\Delta ID_{dp,t} - 0.53\Delta ID_{er,t} + 0.0015\,{}^{pls}f^1_{lr,t-1} + \varepsilon_t$$

(0.037)	(0.025)	(0.00059)	(0.015)
(0.64)	(0.79)	(0.12)	
(0.054)	(0.042)	(0.094)	(1.60*)

$$\Delta ID_t = 0.51\Delta ID_{dp,t} - 0.53\Delta ID_{er,t} + 0.0014\,{}^{pls}_{resid}f^1_{lr,t-1} + \varepsilon_t$$

(0.035)	(0.025)	(0.00041)	(0.015)
(0.67)	(0.80)	(0.098)	(0.06)
(0.13)	(0.025)	(0.49)	(1.59*)

6. Malaysia

$$\Delta MA_t = -0.51\Delta MA_{t-1} - 0.26\Delta MA_{t-2} + \varepsilon_t$$
$$\begin{array}{ccc} (0.088) & (0.088) & (0.023) \\ (0.26) & (0.08) & \\ (0.15) & (0.19) & (1.43^{**}) \end{array}$$

$$\Delta MA_t = -0.55\Delta MA_{t-1} - 0.29\Delta MA_{t-2} - 0.0071\Delta_3{}^{pca}f^1_{lr,t-1} + \varepsilon_t$$
$$\begin{array}{cccc} (0.088) & (0.087) & (0.0059) & (0.023) \\ (0.30) & (0.11) & (0.059) & \\ (0.26) & (0.16) & (0.040) & (1.72^{**}) \end{array}$$

$$\Delta MA_t = -0.46\Delta MA_{t-1} - 0.25\Delta MA_{t-2} - 0.0071\Delta^{pls}f^1_{lr,t-2} + \varepsilon_t$$
$$\begin{array}{cccc} (0.099) & (0.091) & (0.0037) & (0.023) \\ (0.19) & (0.073) & (0.038) & \\ (0.15) & (0.13) & (0.097) & (1.76^{*}) \end{array}$$

$$\Delta MA_t = -0.45\Delta MA_{t-1} - 0.29\Delta MA_{t-2} + 0.0078\,{}^{pls}_{resid}f^1_{lr,t-1} + \varepsilon_t$$
$$\begin{array}{cccc} (0.086) & (0.082) & (0.0016) & (0.021) \\ (0.23) & (0.12) & (0.20) & \\ (0.14) & (0.15) & (0.32) & (1.26) \end{array}$$

Table 3.1 Dynamic forms of PCA and PLS-R y-predicted FCIs that are significant in-sample[76]

	SG	KOR	TW	TH	ID	MA
PCA short run	${}^{pca}f^{1}_{sm,t-2}$	${}^{pca}f^{1}_{sm,t-2}$	${}^{pca}f^{1}_{sm,t-2}$	${}^{pca}f^{1}_{sm,t-4}$	${}^{pca}f^{1}_{sy,t-4}$	${}^{pca}f^{1}_{sm,t-6}$
PCA long run	$\Delta_2{}^{pca}f^{1}_{lr,t-1}$	${}^{pca}f^{1}_{lr,t-1}$	${}^{pca}f^{1}_{lr,t-1}$	$\Delta{}^{pca}f^{1}_{lr,t-1}$	$\Delta_3{}^{pca}f^{1}_{lr,t-2}$	$\Delta_3{}^{pca}f^{1}_{lr,t-2}$
PLS-R y-predicted short run	${}^{pls}f^{1}_{sm,t-1}$	${}^{pls}f^{1}_{sm,t-1}$	${}^{pls}f^{1}_{sm,t-1}$	${}^{pls}f^{1}_{sm,t-1}$	N\A	${}^{pls}f^{1}_{sm,t-1}$
PLS-R y-predicted long run	${}^{pls}f^{1}_{lr,t-1}$	${}^{pls}f^{1}_{lr,t-1}$	${}^{pls}f^{1}_{lr,t-1}$	${}^{pls}f^{1}_{lr,t-1}$	${}^{pls}f^{1}_{lr,t-1}$	$\Delta{}^{pls}f^{1}_{lr,t-2}$

Table 3.2 Forecasting performance among long run PCA FCIs, short run FCIs and benchmark forecasting model

Short run vs. Benchmark												
	SG		KOR		TW		TH		ID		MA	
1-step	1.004 (0.017	1.004 (0.017	1.019 (0.035	1.019 (0.035	1.029 (0.006	1.049 (0.001	1.06 (0.004	1.06 (0.004	1.00 (0.17	1.00 (0.17	1.695 (0.001	1.695 (0.001
2-steps	1.002 (0.048	1.002 (0.048	1.011 (0.066	1.011 (0.066	1.011 (0.064	1.044 (0.001	1.05 (0.004	1.05 (0.004	1.00 (0.14	1.00 (0.14	1.601 (0.001	1.601 (0.001
3-steps	1.001 (-	1.001 (-	1.005 (-	1.01 (0.051	1 (-	1.038 (0.001	1.053 (0.002	1.053 (0.002	1.00 (0.14	1.00 (0.18	1.536 (0.001	1.545 (0.001
4-steps	1 (-	1.001 (-	0.999 (-	1.013 (0.024	0.988 (-	1.036 (0.001	1.046 (0.002	1.046 (0.002	1.00 (0.14	1.00 (0.20	1.549 (0.001	1.586 (0.001
5-steps	1 (-	1.001 (-	0.997 (-	1.015 (0.013	0.982 (-	1.035 (0.001	1.042 (0.003	1.047 (0.002	1.00 (0.13	1.00 (0.25	1.591 (0.001	1.63 (0.001
6-steps	1 (-0.35)	1.001 (-0.35)	0.995 (-	1.016 (0.01*	0.978 (-	1.034 (0.001	1.037 (0.006	1.046 (0.002	1.01 (0.11	1.00 (0.18	1.597 (0.001	1.626 (0.001
Long run vs. Short run												
	SG		KOR		TW		TH		ID		MA	
1-step	0.988 (0.639)	0.988 (0.639)	0.972 (0.751)	0.972 (0.882)	0.977 (0.725)	0.958 (0.983)	0.986 (0.333)	0.986 (0.333)	0.98 (0.32	0.98 (0.32	1.473 (0.002	1.473 (0.002
2-steps	0.987 (0.686)	0.99 (0.632)	0.988 (0.410)	0.972 (0.924)	0.988 (0.456)	0.958 (0.986)	0.991 (0.376)	0.956 (0.885)	0.98 (0.43	0.98 (0.43	1.507 (0.001	1.507 (0.001
3-steps	0.99 (0.632)	0.991 (0.771)	0.998 (0.239)	0.970 (0.951)	0.995 (0.324)	0.96 (0.988)	0.973 (0.697)	0.948 (0.96)	0.97 (0.55	0.98 (0.50	1.532 (0.001	1.532 (0.001
4-steps	0.994 (0.523)	0.986 (0.954)	1.001 (0.222)	0.967 (0.976)	1.004 (0.223)	0.958 (0.992)	0.973 (0.809)	0.95 (0.981)	0.97 (0.64	0.97 (0.55	1.483 (0.001	1.453 (0.001
5-steps	0.995 (0.474)	0.98 (0.991)	1.003 (0.217)	0.964 (0.985)	1.008 (0.209)	0.958 (0.993)	0.966 (0.939)	0.948 (0.995)	0.96 (0.72	0.98 (0.46	1.377 (0.001	1.311 (0.001
6-steps	0.997 (0.439)	0.977 (0.996)	1.002 (0.234)	0.965 (0.975)	1.01 (0.202)	0.957 (0.993)	0.964 (0.986)	0.946 (0.998)	0.96 (0.76	0.98 (0.42	1.331 (0.001	1.207 (0.001

[76] A full list of model specifications can be found in Appendix 3C.

Table 3.3 Forecasting performance among PLS-R y-predicted long run, short run FCIs and benchmark forecasting model

Short run vs. Benchmark												
	SG		KOR		TW		TH		ID		MA	
1-step	1.03 (0.028	1.022 (0.01**	1.022 (0.018	1.026 (0.004	1.039 (0.012	1.049 (0.001	1.038 (0.047	1.025 (0.032	N\	N\	1.997 (0.001	1.025 (0.032
2-steps	1.012 (0.115)	1.016 (0.007	0.999 (0.392)	1.02 (0.002	1.02 (0.052	1.039 (0.001	1.04 (0.062	1.025 (0.022	N\	N\	1.925 (0.001	1.025 (0.022
3-steps	0.998 (0.517)	1.013 (0.008	0.985 (0.752)	1.018 (0.004	1.001 (0.314)	1.034 (0.001	1.035 (0.041	1.027 (0.008	N\	N\	1.778 (0.001	1.027 (0.008
4-steps	0.991 (0.89)	1.011 (0.007	0.978 (0.825)	1.018 (0.003	0.99 (0.641)	1.03 (0.001	1.034 (0.055	1.026 (0.01**	N\	N\	1.727 (0.001	1.026 (0.01**
5-steps	0.986 (0.907)	1.01 (0.006	0.973 (0.853)	1.018 (0.003	0.981 (0.765)	1.026 (0.001	1.03 (0.077	1.022 (0.006	N\	N\	1.668 (0.001	1.022 (0.006
6-steps	0.983 (0.911)	1.008 (0.013	0.971 (0.853)	1.015 (0.006	0.976 (0.803)	1.02 (0.004	1.029 (0.08*)	1.02 (0.012	N\	N\	1.585 (0.001	1.02 (0.012
Long run vs. Short run												
	SG		KOR		TW		TH		ID		MA	
1-step	0.968 (0.894)	0.979 (0.877)	0.972 (0.752)	0.972 (0.883)	0.975 (0.444)	0.967 (0.723)	0.985 (0.032	0.994 (0.007	N\	N\	0.842 (0.003	1.09 (0.001
2-steps	0.981 (0.7)	0.982 (0.807)	0.988 (0.41)	0.972 (0.924)	0.984 (0.242)	0.97 (0.604)	0.959 (0.046	0.968 (0.052	N\	N\	0.901 (0.001	1.187 (0.001
3-steps	0.989 (0.463)	0.98 (0.842)	0.998 (0.239)	0.97 (0.951)	0.995 (0.104)	0.968 (0.636)	0.955 (0.03**	0.951 (0.092	N\	N\	1.01 (0.001	1.218 (0.001
4-steps	0.991 (0.363)	0.976 (0.89)	1.001 (0.222)	0.967 (0.976)	1.001 (0.081	0.967 (0.667)	0.947 (0.029	0.939 (0.186)	N\	N\	1.085 (0.001	1.263 (0.001
5-steps	0.992 (0.324)	0.974 (0.897)	1.003 (0.217)	0.965 (0.985)	1.006 (0.08*)	0.966 (0.654)	0.944 (0.015	0.932 (0.213)	N\	N\	1.142 (0.001	1.278 (0.001
6-steps	0.99 (0.331)	0.973 (0.887)	1.002 (0.234)	0.965 (0.975)	1.007 (0.085	0.968 (0.571)	0.94 (0.009	0.925 (0.261)	N\	N\	1.219 (0.001	1.29 (0.001

Table 3.4 Benchmark vs. PCA vs. PLS-R y-predicted vs. PLS-R r-predicted FCIs' forecasting model

		PLS-R y-predicted vs. PCA	PLS-R r-predicted vs. PLS y-	PCA vs. benchmark	PLS-R y-predicted vs. Benchmark	PLS-R r-predicted vs. Benchmark
SG	1-step	1.003 (0.211)	0.998 (0.577)	0.997 (0.645)	1 (0.277)	0.998 (0.514)
	2-step	1.002 (0.247)	0.997 (0.635)	0.996 (0.706)	0.997 (0.319)	0.999 (0.397)
	3-step	0.998 (0.43)	1 (0.391)	0.994 (0.817)	0.992 (0.502)	0.998 (0.459)
	4-step	0.996 (0.564)	1.003 (0.197)	0.992 (0.897)	0.987 (0.657)	0.997 (0.523)
	5-step	0.994 (0.591)	1.004 (0.138)	0.989 (0.935)	0.983 (0.721)	0.995 (0.581)
	6-step	0.993 (0.628)	1.006 (0.11)	0.987 (0.954)	0.98 (0.771)	0.994 (0.655)
KOR	1-step	0.997 (0.678)	1.003 (0.177)	0.993 (0.678)	0.997 (0.367)	0.994 (0.946)
	2-step	0.999 (0.498)	1 (0.231)	0.989 (0.817)	0.991 (0.575)	0.992 (0.996)
	3-step	1.001 (0.332)	0.998 (0.269)	0.987 (0.891)	0.987 (0.735)	0.989 (0.999)
	4-step	1.002 (0.305)	0.997 (0.287)	0.984 (0.941)	0.984 (0.833)	0.987 (0.999)
	5-step	1.002 (0.317)	0.997 (0.288)	0.982 (0.966)	0.981 (0.884)	0.985 (0.999)
	6-step	1.002 (0.325)	0.997 (0.283)	0.980 (0.976)	0.979 (0.9)	0.983 (0.999)
TW	1-step	1.01 (0.058*)	0.988 (0.881)	1.004 (0.231)	1.014 (0.049**)	0.992 (0.625)
	2-step	1.008 (0.076*)	0.988 (0.856)	0.999 (0.378)	1.007 (0.074*)	0.98 (0.924)
	3-step	1.005 (0.116)	0.99 (0.798)	0.996 (0.502)	1 (0.112)	0.973 (0.992)
	4-step	1.003 (0.161)	0.991 (0.759)	0.993 (0.607)	0.996 (0.156)	0.968 (0.998)
	5-step	1.001 (0.229)	0.991 (0.724)	0.991 (0.672)	0.991 (0.208)	0.963 (0.999)
	6-step	0.999 (0.287)	0.991 (0.688)	0.989 (0.711)	0.988 (0.255)	0.959 (0.999)

TH	1-step	0.973 (0.062*)	1.016 (0.003**)	1.045 (0.072*)	1.018 (0.001**)	1.033 (0.048**)
	2-step	0.987 (0.041**)	1.023 (0.002**)	1.003 (0.351)	0.991 (0.011**)	1.014 (0.199)
	3-step	0.978 (0.054*)	1.028 (0.001**)	0.998 (0.448)	0.977 (0.026**)	1.003 (0.322)
	4-step	0.968 (0.092*)	1.033 (0.001**)	0.993 (0.611)	0.963 (0.063*)	0.994 (0.442)
	5-step	0.958 (0.134)	1.036 (0.001**)	0.992 (0.678)	0.952 (0.102)	0.986 (0.544)
	6-step	0.952 (0.171)	1.04 (0.001**)	0.989 (0.825)	0.943 (0.151)	0.98 (0.628)
ID	1-step	1.015 (0.076*)	1.026 (0.001**)	0.994 (0.376)	1.008 (0.197)	1.034 (0.003**)
	2-step	1.02 (0.071*)	1.036 (0.001**)	0.991 (0.424)	1.01 (0.183)	1.045 (0.001**)
	3-step	1.022 (0.064*)	1.04 (0.001**)	0.99 (0.461)	1.011 (0.182)	1.051 (0.001**)
	4-step	1.022 (0.071*)	1.045 (0.001**)	0.989 (0.499)	1.011 (0.191)	1.056 (0.001**)
	5-step	1.017 (0.1)	1.048 (0.001**)	0.994 (0.434)	1.011 (0.193)	1.059 (0.001**)
	6-step	1.011 (0.168)	1.052 (0.001**)	1.001 (0.308)	1.012 (0.192)	1.064 (0.001**)
MA	1-step	0.639 (0.001**)	1.554 (0.001**)	2.314 (0.003**)	1.477 (0.001**)	2.294 (0.001**)
	2-step	0.713 (0.001**)	1.559 (0.001**)	2.132 (0.003**)	1.52 (0.001**)	2.369 (0.001**)
	3-step	0.851 (0.001**)	1.573 (0.001**)	1.828 (0.008**)	1.556 (0.001**)	2.446 (0.001**)
	4-step	1.069 (0.001**)	1.599 (0.001**)	1.523 (0.011**)	1.627 (0.001**)	2.599 (0.001**)
	5-step	1.168 (0.001**)	1.611 (0.001**)	1.407 (0.011**)	1.643 (0.001**)	2.645 (0.001**)
	6-step	1.299 (0.001**)	1.627 (0.001**)	1.279 (0.001**)	1.662 (0.001**)	2.703 (0.001**)

Table 3.5 A Summary of Table 3.4[77]

Target Economies	PLS-R r-predicted FCIs vs. PCA FCIs	FCIs vs. Benchmark
SG, KOR, TW	4 > 3 > 2	2 > 1, 3 > 1, 4 > 1
TH	4 ≥ 3 ≥ 2	2 ≥1, 3 ≥ 1, 4 ≥ 1
ID	4 < 3 < 2	2 ≥ 1, 3 < 1, 4 < 1
MA	4 < 3 = 2	2 < 1, 3 < 1, 4 < 1

[77] Here, for brevity, 1 refers to benchmark model; 2 refers to PCA FCIs model; 3 refers PLS-R y-predicted FCIs model; 4 refers PLS-R r-predicted FCIs model; ">" denotes that the former model predicts better than the latter model and by the same token for "<" and "=". For example, "4>3" indicates PLS-R r-predicted FCIs model outperforms PLS-R y-predicted FCIs model. '≥' denotes that the former outperforms the latter with weak statistical power. The same notations are used in Table 1.5.

Table 3.6 Subsample forecasting performance

		SG			KOR			TW		
07M5 –08M9	1-step	0.988 (0.758)	1.008 (0.148)	1.005 (0.559)	0.998 (0.817)	1.008 (0.117)	0.989 (0.88)	1.003 (0.812)	1.011 (0.702)	1.008 (0.565)
	2-step	0.981 (0.919)	1.013 (.018**)	1.004 (0.458)	0.99 (0.993)	1.003 (0.461)	0.98 (0.97)	0.99 (0.992)	0.988 (0.942)	0.995 (0.805)
	3-step	0.97 (0.976)	1.02 (.029**)	0.999 (0.604)	0.976 (0.999)	0.998 (0.84)	0.965 (0.99)	0.973 (0.999)	0.966 (0.992)	0.987 (0.98)
	4-step	0.954 (0.983)	1.02 (0.06*)	0.997 (0.606)	0.965 (0.999)	0.994 (0.884)	0.95 (0.998)	0.961 (0.999)	0.949 (0.997)	0.981 (0.998)
	5-step	0.945 (0.981)	1.019 (0.119)	0.997 (0.587)	0.959 (0.999)	0.99 (0.876)	0.941 (0.999)	0.953 (0.999)	0.935 (0.999)	0.975 (0.999)
	6-step	0.947 (0.993)	1.022 (0.188)	0.997 (0.554)	0.957 (0.999)	0.99 (0.82)	0.935 (0.999)	0.949 (0.999)	0.926 (0.999)	0.971 (0.999)
07M5 –09M6	1-step	0.994 (0.511)	1.01 (0.072*)	1.005 (0.148)	1.001 (0.286)	1.007 (0.093*)	0.995 (0.806)	1.009 (0.185)	1.03 (0.101)	1.002 (0.314)
	2-step	0.995 (0.52)	1.016 (0.03**)	1.008 (0.082*)	1.001 (0.313)	1.004 (0.073*)	0.993 (0.959)	1.005 (0.223)	1.017 (0.115)	0.994 (0.53)
	3-step	0.995 (0.524)	1.022 (.015**)	1.01 (0.082*)	1.001 (0.343)	1.004 (0.074*)	0.991 (0.989)	1.004 (0.284)	1.01 (0.164)	0.99 (0.89)
	4-step	0.994 (0.509)	1.025 (.011**)	1.011 (0.066*)	1.001 (0.395)	1.004 (0.102)	0.988 (0.998)	1.003 (0.332)	1.008 (0.214)	0.989 (0.92)
	5-step	0.997 (0.498)	1.028 (.013**)	1.012 (0.07*)	0.999 (0.448)	1.003 (0.179)	0.986 (0.999)	1.003 (0.37)	1.001 (0.343)	0.988 (0.942)
	6-step	0.999 (0.44)	1.03 (.018**)	1.012 (0.083*)	0.999 (0.454)	1.004 (0.193)	0.983 (0.999)	1.003 (0.381)	0.998 (0.389)	0.988 (0.918)
07M5 –10M1	1-step	0.993 (0.637)	1.005 (0.22)	1.001 (0.372)	0.996 (0.611)	0.998 (0.428)	0.994 (0.912)	1.005 (0.284)	1.023 (0.131)	0.997 (0.494)
	2-step	0.99 (0.798)	1.01 (0.165)	1.005 (0.254)	0.994 (0.751)	0.994 (0.67)	0.991 (0.992)	1.001 (0.435)	1.011 (0.231)	0.988 (0.884)
	3-step	0.989 (0.862)	1.012 (0.14)	1.005 (0.267)	0.992 (0.789)	0.991 (0.794)	0.989 (0.998)	0.997 (0.551)	0.999 (0.372)	0.981 (0.991)
	4-step	0.987 (0.876)	1.012 (0.132)	1.005 (0.238)	0.991 (0.816)	0.99 (0.845)	0.987 (0.999)	0.995 (0.636)	0.994 (0.503)	0.978 (0.996)
	5-step	0.987 (0.862)	1.013 (0.141)	1.005 (0.226)	0.99 (0.845)	0.989 (0.886)	0.986 (0.999)	0.994 (0.682)	0.986 (0.699)	0.975 (0.999)
	6-step	0.988 (0.805)	1.013 (0.139)	1.006 (0.21)	0.99 (0.824)	0.988 (0.861)	0.984 (0.997)	0.993 (0.669)	0.98 (0.787)	0.973 (0.998)
		TH			ID			MA		
07M5 –08M9	1-step	1.125 (.026**)	1.082 (.001**)	1.098 (.002**)	1.059 (.063*)	0.974 (.966)	0.954 (.981)	1.197 (.012**)	1.495 (.02**)	0.899 (.999)
	2-step	1.064 (.003**)	1.085 (.001**)	1.106 (.001**)	1.073 (.044**)	0.958 (.997)	0.923 (.997)	1.181 (.044**)	2.018 (.001**)	0.88 (.999)
	3-step	1.041 (.056*)	1.111 (.001**)	1.14 (.002**)	1.067 (.065*)	0.937 (.997)	0.884 (.999)	0.955 (.084*)	1.75 (.001**)	0.866 (.999)
	4-step	1.045 (.079*)	1.111 (.002**)	1.132 (.003**)	1.067 (.097*)	0.923 (.994)	0.853 (.999)	0.758 (.251)	1.838 (.001**)	0.868 (.999)

	5-step	1.029 (0.175)	1.105 (.008**)	1.117 (.006**)	1.07 (0.12)	0.921 (0.981)	0.833 (0.996)	0.798 (.386)	1.82 (.001**)	0.874 (0.997)
	6-step	1.028 (.221)	1.099 (.041**)	1.103 (.016**)	1.082 (0.128)	0.924 (0.939)	0.819 (0.982)	0.776 (0.472)	1.803 (.001**)	0.876 (0.983)
07M5 –09M6	1-step	1.193 (.018**)	1.025 (.035**)	1.049 (.039**)	0.989 (0.394)	1.005 (0.299)	1.014 (0.206)	2.676 (.005**)	2.086 (.023**)	1.105 (.018**)
	2-step	1.114 (.015**)	1.009 (0.153)	1.028 (0.16)	0.988 (0.401)	1.007 (0.281)	1.015 (0.201)	2.443 (.006**)	1.794 (.001**)	1.042 (.036**)
	3-step	1.054 (0.062*)	1.008 (0.193)	1.018 (0.256)	0.991 (0.311)	1.007 (0.259)	1.014 (0.228)	2.044 (.027**)	1.676 (.001**)	0.998 (0.078*)
	4-step	1.044 (0.085*)	1.006 (0.263)	1.007 (0.354)	0.999 (0.207)	1.009 (0.247)	1.012 (0.279)	1.623 (0.067*)	1.763 (.001**)	1.008 (0.129)
	5-step	1.023 (0.185)	1.007 (0.297)	0.998 (0.451)	1.012 (0.111)	1.011 (0.228)	1.007 (0.313)	1.405 (0.116)	1.789 (.001**)	0.993 (0.251)
	6-step	1.016 (0.215)	1.01 (0.318)	0.989 (0.54)	1.024 (0.092*)	1.015 (0.215)	1.007 (0.327)	1.084 (0.184)	1.8 (.001**)	0.988 (0.342)
2007M5 –2010M1	1-step	1.203 (.009**)	1.012 (0.159)	1.046 (.037**)	0.986 (0.533)	0.988 (0.868)	1.023 (0.079*)	2.669 (.004**)	2.103 (.018**)	1.506 (.001**)
	2-step	1.123 (.005**)	0.99 (0.459)	1.026 (0.145)	0.982 (0.576)	0.996 (0.679)	1.026 (0.075*)	2.436 (.004**)	1.769 (.001**)	1.473 (.001**)
	3-step	1.059 (.024**)	0.98 (0.566)	1.016 (0.231)	0.981 (0.588)	0.996 (0.669)	1.025 (0.093*)	2.054 (.013**)	1.666 (.001**)	1.43 (.003**)
	4-step	1.049 (.037**)	0.973 (0.667)	1.007 (0.319)	0.983 (0.601)	0.999 (0.523)	1.023 (0.125)	1.708 (.019**)	1.735 (.001**)	1.436 (.005**)
	5-step	1.027 (0.095*)	0.968 (0.708)	0.999 (0.389)	0.988 (0.559)	1.002 (0.371)	1.019 (0.182)	1.566 (.025**)	1.749 (.001**)	1.4 (.011**)
	6-step	1.02 (0.144)	0.967 (0.691)	0.995 (0.439)	0.993 (0.481)	1.004 (0.219)	1.016 (0.235)	1.417 (.037**)	1.773 (.001**)	1.37 (0.02**)

Table 3.7 Summary of Table 3.10 and Table 3.12

Subsample	SG	KOR	TW	TH	ID	MA
2007M5–2008M9	2>4>3=1	4=3>2>1	4=3=2>1	1>2=3=4	4=3>1>2	4>1>2>3
2007M5–2009M6	1=2>4>3	4=2=1>3	4>1>2=3	4=1>3>2	1>2>4>3	1=4>2>3
2007M5–2010M1	2>1>4=3	4>3>2>1	4>2=3>1	4=3>1>2	2>4>3>1	1=4>3>2
2007M5–2013M9	4>3>2>1	4>3>2>1	4>3>2>1	4>3>2>1	2≥1>3>4	1>2=3>4

Table 3.8 Estimated weights by PLS-R

Market misalign-ment	Indicator Name	SG		KOR		TW		TH		ID		MA	
Bond–equity yield ratios	BE_R_JP	-0.042	-0.113	-0.115	-0.220	-0.062	-0.147	-0.026	0.006	-0.013	0.053	0.029	0.132
	BE_R_UK	-0.040	-0.145	-0.079	0.012	-0.110	-0.127	0.083	0.283	-0.159	0.025	0.011	-0.009
	BE_R_US	-0.099	-0.079	-0.079	-0.023	-0.102	-0.171	-0.096	0.098	-0.153	-0.025	0.032	0.008
Covered Interest Parity indicators	CIP_JP	0.051	0.083	0.025	-0.241	0.085	-0.011	-0.110	-0.249	0.063	-0.134	0.071	0.120
	CIP_UK	-0.117	0.078	-0.098	-0.265	-0.071	-0.137	-0.223	-0.290	0.118	-0.004	0.067	0.101
Equity–commodity price ratios	ECPI_R_JP	0.001	0.050	-0.059	-0.018	-0.040	-0.022	0.068	0.196	-0.040	0.055	0.074	0.039
	ECPI_R_UK	0.022	0.076	0.066	0.249	-0.006	0.135	-0.098	-0.050	-0.127	0.087	-0.107	-0.163
	ECPI_R_US	0.073	0.178	0.148	0.261	0.092	0.210	-0.027	-0.047	-0.162	-0.065	0.009	-0.102
Yield structures of bond market	Gov_SP_DE	-0.002	-0.023	0.106	0.140	0.036	-0.001	0.191	0.223	-0.015	-0.144	0.046	0.091
	Gov_SP_JP	0.101	-0.163	0.046	0.043	0.024	-0.102	0.316	0.324	0.149	-0.012	-0.054	0.107
	YieldCurve_R_UK	-0.044	-0.092	-0.014	-0.074	-0.028	-0.075	0.044	-0.006	-0.097	-0.073	0.046	0.081
	Gov_SP_UK	0.247	-0.107	0.180	0.030	0.205	0.024	0.380	0.320	-0.114	-0.285	0.237	0.315
	Gov_SP_US	0.161	0.066	0.181	-0.129	0.205	0.009	0.045	-0.092	-0.022	-0.210	0.145	0.176
	IssML_R_JP	0.180	0.380	0.175	0.181	0.197	0.379	0.253	0.109	-0.322	-0.097	-0.168	-0.230
Yield structures of money market rate	MRate_SP_JP	-0.116	-0.144	-0.050	0.129	-0.059	0.096	-0.048	-0.054	0.420	0.297	-0.172	0.142
	MRate_SP_UK	0.203	-0.057	0.175	0.138	0.219	0.070	0.142	-0.022	0.059	0.050	0.024	0.098
Equity market	S&P_R_US	0.160	0.064	0.104	-0.090	0.161	0.109	0.166	0.031	0.142	-0.044	0.321	0.342

TED spread	TED_SP_JP	-0.185	-0.056	-0.194	-0.302	-0.133	-0.161	-0.160	-0.154	0.507	0.286	-0.610	-0.277
	TED_SP_UK	-0.248	-0.134	-0.233	-0.293	-0.160	-0.204	-0.177	-0.177	-0.239	0.167	-0.120	-0.153
	TED_SP_US	-0.277	-0.303	-0.133	0.033	-0.166	-0.104	0.035	0.246	-0.036	0.089	0.001	-0.015
Forex indicator	ERFER_SP_UK	-0.042	0.243	0.121	0.042	0.124	0.149	0.000	-0.066	0.078	0.048	0.047	0.114
Money–bond interest rate ratios	MB_R_EU	-0.186	-0.181	-0.299	-0.207	-0.251	-0.177	-0.221	-0.146	0.039	0.225	-0.177	-0.299
	MB_R_JP	-0.180	-0.199	-0.213	-0.294	-0.138	-0.177	-0.221	-0.226	0.137	0.306	-0.247	-0.121
	MB_R_UK	-0.239	0.009	-0.214	-0.038	-0.230	-0.071	-0.365	-0.302	0.061	0.252	-0.236	-0.313
	MB_R_US	-0.173	-0.146	-0.196	0.092	-0.210	-0.051	-0.042	0.126	0.032	0.191	-0.119	-0.153
Derivative indicator	TSEO_R_JP	-0.227	-0.235	-0.242	-0.130	-0.262	-0.278	-0.014	0.237	-0.194	0.086	-0.079	-0.068
	FuOption_R_JP	-0.340	-0.147	-0.270	-0.060	-0.321	-0.277	-0.216	-0.001	-0.049	0.211	-0.094	-0.179
Money–inflation rate ratios	RRate_3m_UK	-0.278	-0.066	-0.270	-0.240	-0.251	-0.262	-0.235	-0.121	0.090	0.297	-0.112	-0.132
	RRate_3m_US	-0.205	-0.158	-0.216	0.007	-0.222	-0.136	-0.038	0.172	-0.027	0.171	-0.089	-0.121
	RRate_3m_JP	-0.116	-0.041	-0.157	-0.280	-0.092	-0.146	-0.152	-0.145	0.260	0.362	-0.244	-0.067
Housing–equity price ratios	HPEP_R_UK	0.169	0.304	0.199	0.037	0.243	0.249	0.161	-0.024	0.038	-0.089	0.168	0.215
	HPEP_R_US	0.014	-0.058	-0.064	-0.234	0.012	-0.096	0.092	0.059	0.130	-0.030	0.128	0.216
	ComPaperF_R_US	-0.174	-0.269	-0.188	-0.123	-0.203	-0.265	-0.126	0.029	0.009	0.111	-0.043	0.051
Banking sector indicators	ComBLoanF_R_US	-0.026	0.307	0.034	0.104	-0.008	0.066	0.040	0.102	-0.237	-0.146	0.098	0.111
	LD_R_US	-0.256	-0.217	-0.286	-0.113	-0.300	-0.294	-0.196	0.055	-0.053	0.054	-0.154	-0.209

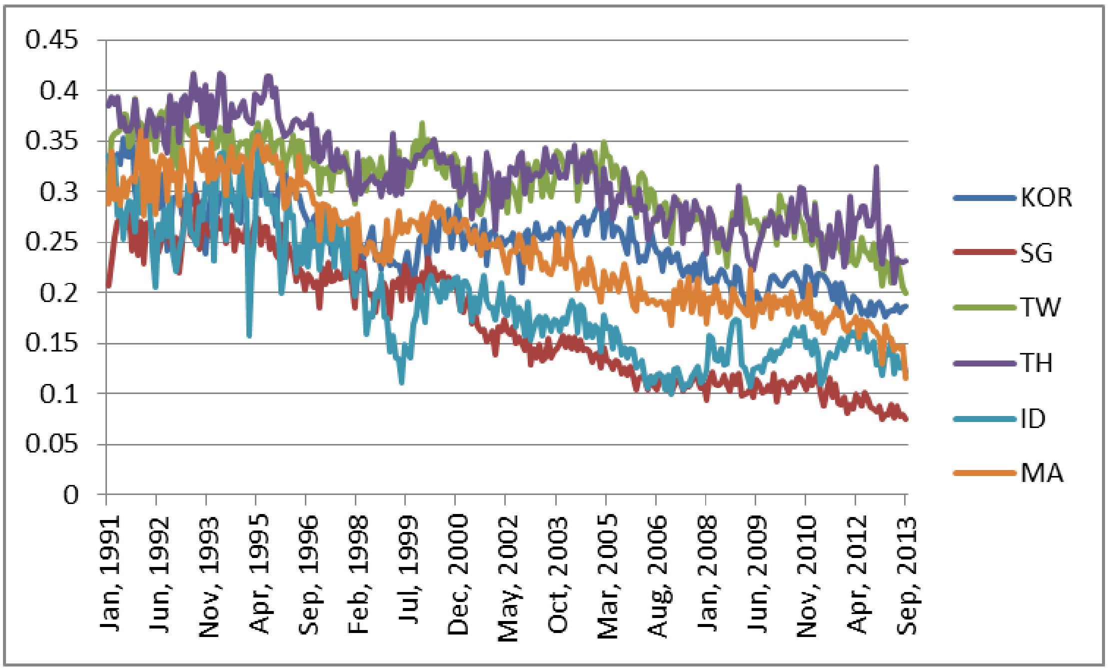

Figure 3.1 Proportion of import volume from Japan

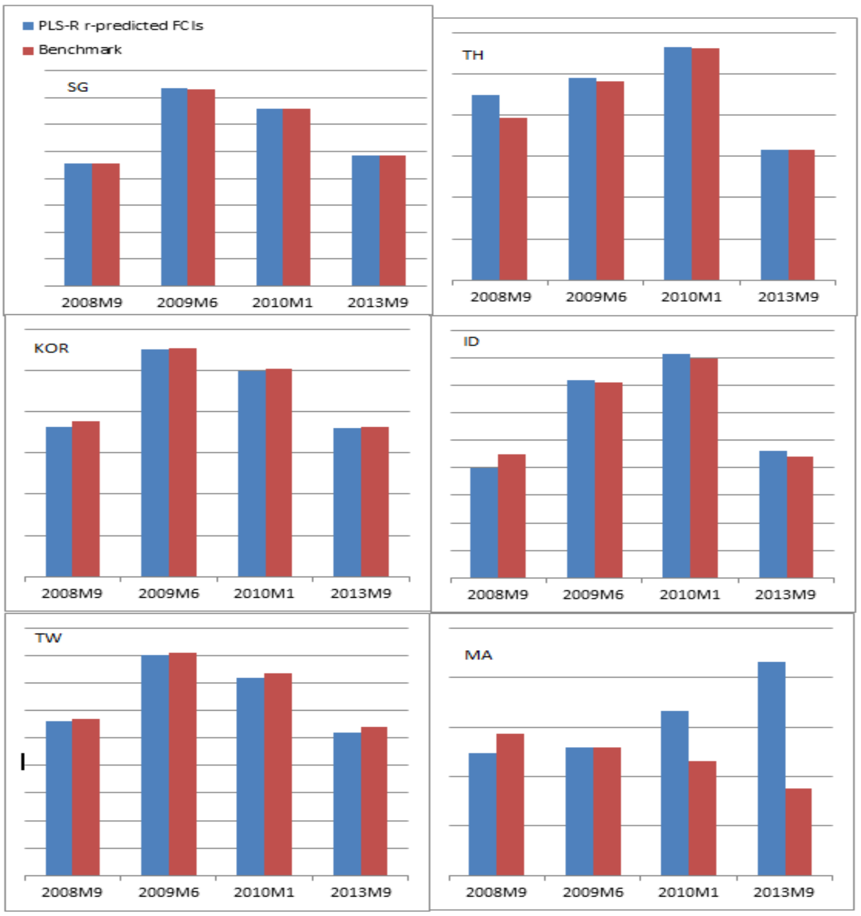

Figure 3.2 RMSFE regarding six target economies

Chapter 4 A. Concatenated SDS-PLS Approach

4.1 Introduction

Based on the superior forecasting performance of PLS-R FCIs' against the PCA-FCIs' forecasting model, which is found in Chapter 3, this chapter carries out a further experiment with respect to PLS-R FCIs only. A Concatenated Simple Dynamic Sparse PLS (henceforth, CSDS–PLS) method is proposed. Compared to the PLS-R FCIs constructed in Chapter 3, it is innovative in two respects: (1) FCIs are concatenated along with a fixed-window (12-months) update of weight estimates, instead of once-for-all fixed weight estimates; and (2) a Simple Dynamics Sparse PLS method (SDS–PLS) is proposed to model desynchronized dynamics at the indicator level. For brevity, the concatenated FCIs estimated by the Simple Dynamic Sparse method are termed as CSDS–PLS FCIs.

The two innovations are proposed in order to solve two issues related to the fixed-weighted PLS-R FCIs constructed in Chapter 3.[78] The two issues are stated as follows: First, the fixed-weighted FCIs have the in-sample (91M1–-07M4) weight estimates fixed for the entire out-of-sample period (07M5–13M9). The FCIs had their weights fixed for such a long time (more than 6 years) that they are unlikely to be applicable in practical forecasting and are threatened by the 2008 crisis, in the sense that weights are unlikely to be constant during the 2008 crisis. Second, PLS-R FCIs assume over-restrictive, synchronized dynamics among all indicators.

This chapter has two main tasks corresponding to the two innovations. First, in order to test the superiority of CSDS–PLS FCIs, predictive tests of CSDS–PLS vs. PLS-R y-predicted and r-predicted FCIs, and the benchmark model are carried out. Second, it is able to analyse the desynchronizsed leading effect of financial indicators due to the CSDS–PLS method.

This chapter is organized as follows. Section 4.2 explains how FCIs are concatenated. Section 4.3 introduces CSDS–PLS method by highlighting how desynchronized disaggregate dynamics is modelled. Section 4.4 specifies the empirical design. Section 4.5 discusses the empirical results—the forecasting performance of CSDS–PLS FCIs vs. PLS-R FCIs and of CSDS–PLS FCIs vs. the benchmark model through subsample predictive tests; Section 4.6 discusses the leading role of financial indicators.

[78] Unless elaborated, PLS-R FCIs refer to the two types of PLS-R FCIs used in Chapter 3.

4.2 Concatenation

The concatenation method is similar to the construction of commonly used aggregate indices, and therefore an exemplification of the well-known Consumer Price Index can help understand the rationale of concatenation. According to Boskin et al. (1998), various surveys, such as Point-of-Purchase Survey and Consumer Expenditure Survey, reveal the proportion of a consumer's income actually spent on each item; then these items are defined as a 'basket' of goods and the proportion (corresponding to weight estimates of FCIs) to construct the aggregated CPI is fixed for several years. In a word, CPI has weights that are comparatively several-year fixed for aggregation purposes, but still enjoys the flexibility in terms of weight updates.

Through concatenation, FCIs can be updated in a similar fashion as CPI. Exhibit 4.1 illustrates how FCIs are recursively concatenated.

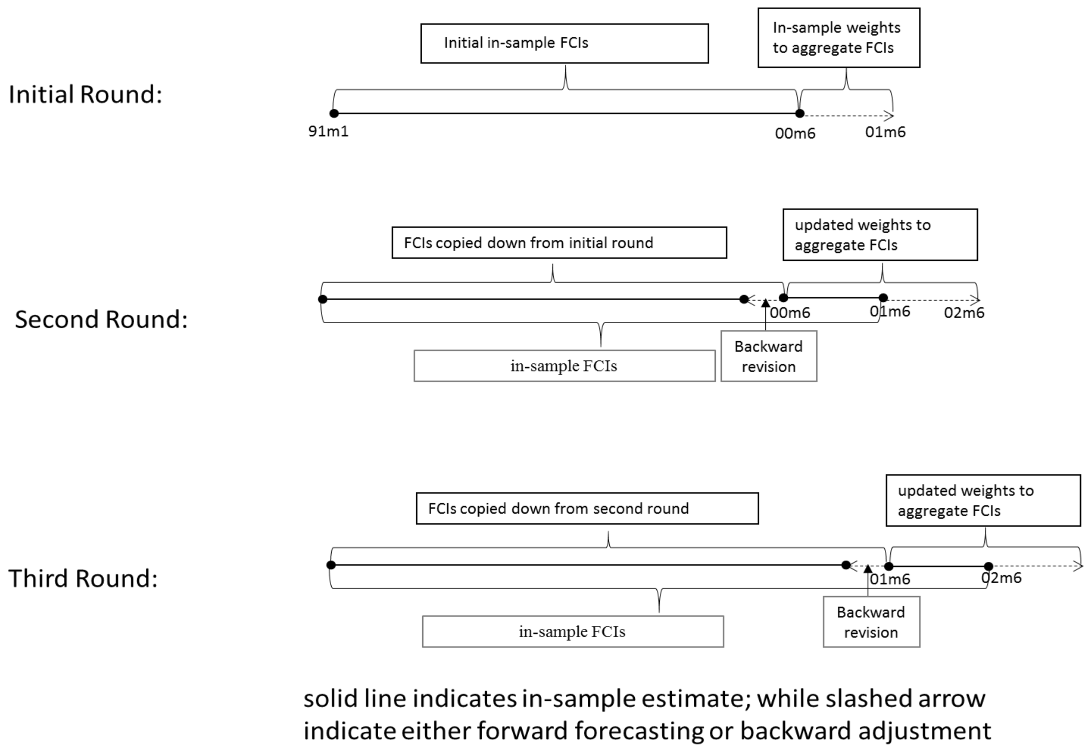

Exhibit 4.1 Diagram Illustration of Concatenation

1st round Because this chapter intends to respectively compare the predictive power of FCIs pre-2008 crisis and post-2008 crisis, the sample size for the out-of-sample encompassing test should be roughly the same for each. For this reason, weights to construct initial round FCIs are initially estimated from 91M1–00M6 such that at least 8 years of data are saved for out-of-sample encompassing testing pre-2008-crisis, compared to only 1 year (07M5–08M9) data for out-of-sample encompassing testing in Chapter 3. The in-sample weight estimates are then used to construct 1-year-ahead forecasted FCIs.[79]

2nd round The previous out-of-sample data, that is, 00M7–01M6, are available *ex ante*. The second round FCIs are then concatenated by two parts. The initial round FCIs are directly copied down to be the 91M1–00M6 part of the FCIs in second round; weights estimated from 91M1–01M6 are used to construct the 00M7–01M6 part of FCIs in the second round. A moderate backward revision is then used to eliminate the intercept gap in the concatenation process. Within 00M1–00M6, the difference of the initial round and the second round FCIs is used to measure the intercept gap. Finally, and similar to the initial round, the updated weights are used to construct the 1-year-ahead forecasted FCIs.

3rd round The third FCIs are constructed similar to second round: the 01M7–02M6 part of the data are included in-sample; the second round FCIs are copied down to be the 91M1–01M6 part of third round FCIs; updated weights are used to construct the 01M7–02M6 part of third round FCIs. From an alternative perspective, three weight estimates are used to construct third round FCIs—the first round weight estimates for the 91M1–00M6 part, the second round weight estimates for the 00M7–01M6 part, and, finally, the third round updated weights for the 01M7–02M6 part, namely, the third round in-sample updated data.

This process is repeated until the final round (13th round) FCIs are constructed: 11M7–12M6 data are included in-sample and updated weights are to construct the 12M7–13M6 *ex ante* FCIs. In a word, the concatenated FCIs have advantages of both the fixed-weighted and the (DFM) time-varying FCIs used in last two chapters. That is, similar to the DFM time-varying FCIs construct in Chapter 2: the concatenated FCIs are recursively estimated and forecasted in order to incorporate disaggregate information timely; similar to the fixed-weighted FCIs, the concatenated FCIs are constructed to be time-invariant at the aggregate level in the recursive estimation process and have the same in-sample weights to construct the in-sample part FCIs (1 year long) and forecast the out-of-sample part of FCIs (1 year long).

[79] FCIs are pseudo *ex ante* in that although weights are in-sample estimated value, the real value (*ex post*) of financial indicators is used to construct FCIs.

4.3 Simple Dynamic Sparse of disaggregate financial indicators

Chapter 3 specified a synchronized disaggregate dynamics through the PLS-R method.

$$X_{t-1} = FV' + \epsilon \tag{3.1'}$$

$$Y_t = UC' + u \tag{3.2'}$$

From Equations (3.1') and (3.2'), weight estimators were derived by the Iterative Least Squares algorithm.

$$W^T = Y_t^T X_{t-1} \tag{4.1}$$

In order to reflect the desynchronized disaggregate dynamics among all financial indicators, this chapter expands the financial indicator matrix, X_{t-1}, by including lags from 1-month to 6-months.

$$X_{exp} = (\mathrm{x}_{1,t-1} \quad \mathrm{x}_{1,t-2} \quad \cdots \ \mathrm{x}_{1,t-6}, \cdots, \mathrm{x}_{N,t-1}, \cdots, \mathrm{x}_{N,t-6}) \tag{4.2}$$

Then the expanded financial indicator matrix, X_{exp}, is used to replace the original X_{t-1} matrix in Equation (4.1)

$$W_{exp}^T = Y_t^T X_{exp} \tag{4.3}$$

In Equation (4.3), weight estimates are allocated to all lags (1-month lag to 6-month lag) of X.

It seems that the FCIs that can model desynchronized disaggregate dynamics can therefore be constructed.[80] However, the largely (6-folded) expanded indicator matrix gives rise to an issue. As noted by Mehmood et al. (2012) and Chun and Keles (2010), when a large number of irrelevant indicators are included, PLS-R FCIs include too much noisy information. Particularly, when the ratio of number of indicators to sample size (N/T in this thesis) is high, the estimate of PLS-R FCIs is no longer asymptotically consistent. This is especially the case for X_{exp} , because the chance is high that the inclusion of all 6 lags are redundant to model the disaggregate dynamics and therefore a lag selection is necessary. Multiple methods are suggested in recent literature on how to select indicators in a PLS framework. (Fuentes et al. 2014b) propose a hard

[80] This logic can be understood conversely. Only when the ranking of lag phases is the same for all financial indicators can the synchronized dynamics be still assumed.

threshold: a targeted variable is regressed on each indicator[81] and if the OLS estimate of weight is insignificant (at a certain significance level), the indicator is screened out. As an alternative, S\a ebø et al. (2008) and Tibshirani et al. (2003) proposed a soft threshold: if the absolute value of a certain weight estimate is smaller than a given scalar δ, such weight is reset to zero. It is notable that the forecasting performance of PLS factors is used to reversely decide δ[82].

From Exhibit 4.2, a modified soft threshold is adopted in this chapter for simplicity and practicality.[83] Instead of a unique δ, for an individual financial indicator, the lag with largest absolute weight estimate (among all 6 lag phases) is retained and the other lags (of this indicator) are screened out. The resulting sparse indicator matrix X_{sparse} is then used to construct CSDS–PLS factors. An example of such dynamic sparse method is illustrated from Exhibit 1. The 4-month lagged of the first financial indicator (x_1), $\mathrm{x}_{1,\mathrm{t}-4}$, is retained, because it has the largest absolute weight estimate among all 6 lags of x_1. For the same reason, the 6-month lagged of nth financial indicator, $\mathrm{x}_{\mathrm{n},\mathrm{t}-6}$, is retained among all 6 lags of x_n.

[81] Note that in this chapter, the indicators should be 35×6, that is, 35 indicators with each up-to-6 lag phases.
[82] In statistics, Bootstrap bundled with Cross validation is explicitly used to evaluate the forecasting performance of aggregated PLS factors.
[83] Hard threshold may cause the dropout of all 6 lags of a financial indicator and, therefore, the table-making is very difficult for the disaggregate analysis in Section 6. Also, since the predictive power of PLS-R factors is evaluated regarding quite a few[83] out-of-sample intervals, an extreme large volume of calculations is required if a unique δ (soft threshold) is used to filter out financial indicators, and, therefore, was not adopted in this chapter.

Exhibit 4.2 Examples of CSDS–PLS

Exhibit 4.3 summarizes the methodological difference among three types of PLS-R FCIs. Due to the Simple Dynamic Sparse method, SDS-PLS FCIs can model desynchronized disaggregate dynamics while PLS-R y-predicted and r-predicted FCIs cannot.

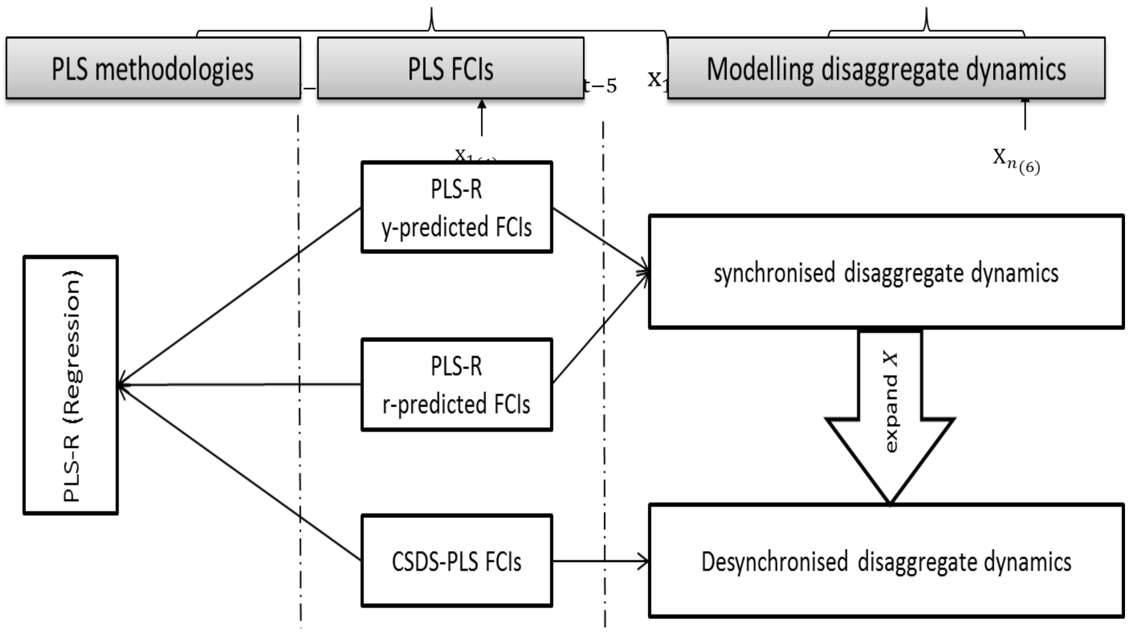

Exhibit 4.3 Comparing CSDS–PLS FCIs with PLS-R y-predicted, r-predicted FCIs

4.4 Experimental design

This section explains the experiment design prepared for the following empirical analysis, namely Section 4.5 and Section 4.6. Basically, the experimental design is elaborated concerning an out-of-sample encompassing test of CSDS–PLS FCIs vs. PLS-R (y-predicted and r-predicted) FCIs models and that of CSDS–PLS FCIs vs. the benchmark models.

Prior to a discussion on experimental design specific for each of two out-of-sample encompassing tests, three general settings to be also used in Chapter 5 are listed.

1) All types of FCIs are constructed from long-run financial indicators because these financial indicators have been proved to have more predictive power than short-run indicators in Chapter 3.

2) Because of the shortage in the observations of a macro variable, both target import price index and macro predictors, with respect to Indonesia and Malaysia are available only since late 20th century, the remaining four economies—Singapore, Korea, Taiwan, and Thailand are reserved for empirical analysis.

3) In terms of the out-of-sample part of FCIs, on the one hand, real (*ex post*) value is used for the out-of-sample part of world export price index; the FCIs are constructed by the *ex post* value of financial indicators multiplied by the in-sample estimated weights. On the other hand, other macro predictors are *ex ante* forecasted from AR models (see Chapter 3). It is notable that the use of the world export price index puts the benchmark model on an extra margin (compared to the related settings in Chapter 3). This is because in the benchmark models[88] for Singapore and Thailand, the world export price index are in-sample significant in the contemporaneous, differenced form, $\Delta X_{wp,t}$, while only the lagged financial indicators are allowed to construct CSDS–PLS FCIs. That is to say, in terms of predictive power, $\Delta X_{wp,t}$ benefits more than CSDS–PLS FCIs, because the more timely information is used—not to mention fact that the release date of macro predictors always lag behind that of financial indicators.

The empirical settings for predictive test of CSDS–PLS FCIs vs. PLS-R y-predicted and r-predicted FCIs are:

- Only the first CSDS–PLS factor is used to represent FCIs, because the PLS-R y-predicted and r-predicted factor was also used to represent FCIs in Chapter 3.
- The predictive test is based on the 07M7–08M6 out-of-sample interval but not the whole out-of-sample period (07M7–13M9). This is because PLS-R y-predicted and r-predicted FCIs will be in unfavourable positions against CSDS–PLS FCIs. Specifically, as illustrated in Section 4.2, weights are re-estimated from a recursively enlarged subsample—the 91M1–08M6 subsample to construct the 08M7–09M6 out-of-sample part of CSDS–PLS FCIs. By contrast, weights to construct PLS-R (y-predicted and r-predicted) FCIs are estimated from subsample 91M1–07M6 and are fixed for the entire out-of-

[88] Despite the shifts recorded in Table 1, the specification of the benchmark forecasting models is basically the same as those in Chapter 2 and, therefore, omitted.

sample period. In this sense, CSDS–PLS FCIs, when compared to PLS-R FCIs, use *ex post* information assumed in constructing the PLS-R FCIs.

The empirical settings for the predictive test of CSDS–PLS FCIs vs. the benchmark model are:

- Instead of using only one factor, the first three CSDS–PLS factors are allowed to represent FCIs. Given that desynchronized disaggregate dynamics is allowed to be modelled in constructing FCIs, it is appropriate to reconsider the trade-off when including more CSDS–PLS factors as proxy for FCIs, compared to the use of only first PLS-R FCIs in last chapter. On one hand, Gadanecz and Jayaram (2008) argued that multiple factors are used by central banks, but only in the sense that each can represent a subset of the whole financial conditions, such as banking stability index, while the second and third CSDS–PLS factors do not have a clear-cut economic interpretation at the aggregate level. On the other hand, in addition to the possibility that the second and third CSDS–PLS factors may further improve the forecasting accuracy, which is quite high, the second and third CSDS–PLS factors can also contribute to the economic interpretation at the disaggregate level—to what extent can the external financial indicator lead the import price index? As to be seen in Section 4.5, when predicting the Korean import price index for the 03M7–04M6 out-of-sample interval, the 4-month lagged yield structure of US bond market (GOV_SP_US) survives[89] and has its weight estimate equal to 0.166 (with 0.06 standard error) in the construction of the first CSDS–PLS factor, and the 2-month lagged of the same indicator survives and has its weight estimate equal to 0.184 (with 0.05 standard error) in the construction of the third factor. While the estimator of OLS coefficients results from the final forecasting model, the coefficient of the 1-month lagged first factor is 0.0017 (with $6.7e^{-4}$ standard error), the coefficient of 1-month lagged third factor is 0.0051 (with $10e^{-4}$ standard error), and the coefficient of 5-month lagged third factor is 0.004 (with $9e^{-4}$ standard error).[90] It therefore can be concluded that $\Delta_2 GOV\_SP\_US_{t-2}$ is the survived form, based on the calculations on all the 5 weights listed above. By using the first CSDS–PLS factor only, the dy-

[89] The largest weight within lag phases of an individual indicator; see Chapter 4.

[90] The forecasting models are specified as:

$$\underset{}{\Delta KOR_t} = \underset{(0.063)}{0.26}\Delta KOR_{wp,t} + \underset{(0.076)}{0.65}\Delta KOR_{dp,t} - \underset{(0.005)}{0.014}\left(KOR - KOR_{wp}\right)_{t-1} - \underset{(0.00067)}{0.0017}\,{}^{pls}f^{1}_{t-1} + \underset{(0.001)}{0.0051}\,{}^{pls}f^{3}_{t-1} - \underset{(0.0009)}{0.0040}\,{}^{pls}f^{3}_{t-5} + \varepsilon_t$$

namic forms of GOV_SP_US are misleading due to the omitted second and third CSDS–PLS factors.

- In order to see whether concatenation can maintain the predictive power, successive predictive tests corresponding to the 1-year updating rounds of concatenation are naturally carried out. Also, there are 8 out-of-sample intervals pre-2008 crisis ranging from 00M7–08M6 and 8 out-of-sample intervals post-2008crisis ranging from 08M7–13M6. And, both CSDS–PLS FCIs and the benchmark forecasting models are re-estimated each round. This is because a forecasting model updated frequently is more likely to apply in practice—especially concerning the 2008 crisis when the dynamic form of CSDS–PLS FCIs are quite likely to shift.

After the above discussion on the empirical settings for the two types of predictive tests, the two types of tests can be more accurately described. In Section 4.5, by using the 1-year out-of-sample interval, 07M7–08M6, the superiority of CSDS–PLS FCIs vs. PLS-R (y-predicted and r-predicted) FCIs pre-2008 crisis is first evaluated. By using successive out-of-sample intervals, the superiority of CSDS–PLS FCIs against the benchmark model is then evaluated.

4.5 Empirical results I

This section is organized in order to test the superiority of the concatenation method. Subsection 4.5.1 discusses the in-sample model specification; Subsection 4.5.2 investigates the forecasting performance of CSDS–PLS FCIs vs. PLS-R FCIs (constructed in Chapter 3), and Subsection 4.5.3 carries out successive predictive tests of CSDS–PLS FCIs vs. the benchmark model.

4.5.1 In-sample modelling result

From Table 4.1, different specifications of forecasting models are observed corresponding to all out-of-sample intervals (13 in total). Due to the experimental design: 1-year out-of-sample data in this round will become in-sample available when re-estimating the forecasting model in the next round; large-scale shift of specification for the CSDS–PLS FCIs' forecasting models implies the forecasting failure of CSDS–PLS FCIs. In this sense, an elaborate investigation on model specifications corresponding to all out-of-sample intervals can help identify the timing of a potential forecasting failure.

The detailed results from Table 4.1 are:

- There are more shifts of (CSDS–PLS) FCIs than macro predictors during the 2008 crisis. In particular, Singapore, Korea, and Thailand all see different factors survived post-2008 crisis. Taking Singapore as an example, 2-months and 6-months lagged third factor are in-sample significant pre-2008 crisis, while the first factor in 2-months and 5-months differenced from are in-sample significant post-2008 crisis.

Among macro predictors, the world export price index is most likely to shift with respect to the four target economies. For example, its 1-month lagged co-integration with the target, the import price index, becomes in-sample significant for Thailand, while the error correction term becomes in-sample insignificant for Taiwan during the 2008 crisis. Furthermore, the world export price index in the differenced form becomes in-sample significant during the 2008 crisis for Singapore. This is not a surprising result considering the fact that world export price index reflects the world-wide import volume and, therefore, is more susceptible to external financial market volatility during 2008 crisis than other macro predictors.

4.5.2 Predictive tests of CSDS–PLS FCIs vs. PLS-R y-predicted and r-predicted FCIs

Table 4.2 reports the out-of-sample encompassing tests of CSDS–PLS vs. PLS-R y-predicted FCIs' forecasting model and of CSDS–PLS vs. PLS-R r-predicted FCIs' forecasting model. It shows that CSDS–PLS FCIs are much superior against PLS-R y-predicted FCIs' forecasting model with respect to all four target economies. Even though CSDS–-PLS FCIs do not directly target the residual information (the import price index purged by macro predictors), as PLS-R r-predicted FCIs do, CSDS–PLS FCIs outperform the PLS-R r-predicted FCIs' forecasting model with respect to Singapore and Thailand.

A clue to explain such consistent superior performance can be found from Figures 4.1 and 4.2. Figure 4.1 shows that the time series pattern of CSDS–PLS FCIs during the 1991–2000 subsample is more flattened than PLS-R y-predicted and PLS-R r-predicted FCIs. The flattened figure is due to the location shift observed in the construction of the CSDS–PLS FCIs. Specifically, From Table 4.2, the CSDS–PLS FCIs are constructed by first using the 91M1–00M6 subsample; when they are updated for the 00M7–01M6 interval, a significant location shift occurs. Furthermore, for CSDS–PLS FCIs, the location shift at the disaggregate level corresponds to the non-constant weight estimates. By construction, however, the PLS-R y-predicted and r-predicted FCIs neglect the non-constancy issue by estimating the weights from the 91M1–07M4 subsample.

In summary, despite the small sample issue, this subsection shows the superior forecasting performance of CSDS–PLS FCIs against PLS-R y-predicted and r-predicted FCIs with respect to all four target economies.

4.5.3 Predictive test of CSDS–PLS FCIs vs. the benchmark FCIs

Before discussing the empirical results, four test statistics are explained first because they are used both in this chapter and Chapter 5 to evaluate the forecasting performance of FCIs.

1. SRRMSE: a ratio of RMSFE from a moving window. In this chapter (and the next chapter), the moving window is a fixed 1-year out-of-sample interval, say 07M7–08M6.
2. P-SRRMSE: the p-value of MDM statistics corresponding to the moving window.
3. CRRMSE: a cumulative ratio of RMSFE from a cumulative window. In this chapter (and the next chapter), the cumulative window is an accumulation of the 1-year out-of-sample interval. For example, the 07M7–09M6 cumulative window is a sum of the 07M7–08M6 and 08M7–09M6 out-of-sample intervals.
4. P-CRRMSE: the p-value of MDM statistics corresponding to the cumulative window.

In addition to CRRMSE and P-CRRMSE, SRRMSE and P-SRRMSE are mainly used in this chapter and Chapter 5. The necessity of SRRMSE and P-SRRMSE can be found from Chapter 3. Specifically, Chapter 3 postulates that the predictive power of FCIs should be regained within a period the after 2008 crisis, while judging by the test statistics, which are in fact CRRMSE and P-CRRMSE, the regaining phenomenon is not obvious. This is because when large forecasting failure of the FCIs' forecasting model is observed during 2008 crisis, it cannot be averaged out in a short time and therefore the CRRMSE and P-CRRMSE continuously favour the benchmark model over the FCIs' forecasting model, even though FCIs quickly regains their predictive power if judged by the SRRMSE and P-SRRMSE statistics. In summary, the forecasting failure of FCIs can be isolated and won't affect the following predictive test if SRRMSE and P-SRRMSE are used. And therefore, the predictive test of CSDS–PLS vs. the benchmark model is mainly evaluated by SRRMSE and P-SRRMSE.

Pre-2008 Crisis

From Table 4.3 to Table 4.6, since the forecasting performance of CSDS–PLS FCIs pre-2008 crisis is quite different from that of those post-2008 crisis, the empirical results are, respectively, discussed pre-2008 crisis and post-2008 crisis.

For the out-of-sample intervals pre-2008 crisis, SRRMSE and P-SRRMSE recorded from Table 4.3 to Table 4.6 show that CSDS–PLS FCIs' forecasting models in general outperform the benchmark models with respect all four target economies.

Let me now focus on the few intervals for which CSDS–PLS FCIs fail to outperform the benchmark model and postulate the economic reasons. As to the 8 out-of-sample intervals, Singapore experiences the forecasting failure of CSDS–PLS FCIs at only one interval; for Korea and Taiwan, failture at 3 intervals; and for Thailand, at 4 intervals. The main finding is that 00M7–01M6 is the common failed out-of-sample interval. Since this period is quite near to the ACC (see Chapter 1), it is postulated here that the prolonged effect of ACC has caused the decoupling of domestic macro markets from external financial markets of all these four economies. Such a postulate can be further verified by the degree of underperformance of the FCIs' forecasting model of the four economies. That is, the degree of underperformance of CSDS–PLS FCIs' forecasting model for Korea and Thailand case is higher than that of Singapore and Taiwan. In reality, Korea and Thailand are well known for their currencies being deflated and their macro economies worsening the most during ACC.[94] Moreover, studies such as Chen (2000) and Jin (2000) revealed that Taiwan was almost immune to ACC and Singapore weathered the ACC better than most Asian economies. Additionally, it is postulated that the China's entry into WTO caused the more severe worsening of FCIs in Korea and Taiwan for the 02M7–03M6 out-

[94] The ACC begans in Thailand and ended in Korea, as is widely known; Indonesia was even more severely affected by ACC but because of the shortage of data, it is not included as a target economy for this chapter.

of-sample interval, as the two economies saw their import volume from China occupy a larger portion of their respective economies than in Singapore and Thailand.

The economic phenomenon used to explain the forecasting failure of the CSDS–PLS FCIs pre-2008 crisis, can also shed light on the post-crisis failure. In essence, ACC, China's entry into WTO and the 2008 crisis can cause the decoupling of domestic market and external financial market but only at different degrees.

Post-2008 Crisis

2008 crisis, but there are signals that the predictive power of CSDS–PLS FCIs is gradually re-gained post-2008 crisis, that is, a result similar with those in Chapter 3. Because of the unprecedented depth and scope of the 2008 crisis, the location shift, which is used to explain the forecasting failure of PLS-R (y-predicted and r-predicted) FCIs during the 2008 crisis, can also be used to explain the forecasting failure of CSDS–PLS FCIs during the 2008 crisis. From Figure 4.3, all four of the target economies see a significant location shift as to the 08M7–09M6 out-of-sample interval than the 09M7–10M6 and 10M7–11M6 intervals. Moreover, from Table 4.1, the in-sample significant CSDS–PLS FCIs see a dynamic transformation from level to difference during the 2008 crisis with respect to Singapore, Korea, and Taiwan while CSDS–PLS FCIs remain in the level form with respect to Thailand. As illustrated in Chapter 3, the differenced CSDS–PLS FCIs difference out the location shift while the level CSDS–PLS FCIs keep the location shift. This reason exactly explains the significant forecasting failure of the CSDS–PLS FCIs' forecasting model with respect to Thailand.

According to Wang and Whalley (2010), there was a solid economic rebound in 2010 after a sharp fall between late 2008 and all of 2009 with respect to the four target economies, that is, following the same rationale to explain the forecasting failure of the CSDS–PLS FCIs pre-2008 crisis. For brevity, for this chapter, the intervals that CSDS–-PLS FCIs fail to improve the forecasting performance are termed as unstable intervals and the intervals that the CSDS–PLS FCIs outperform the benchmark model are termed as stable intervals.

From Table 4.3 to Table 4.6, the SRRMSE and P-SRRMSE statistics show that the predictive power of CSDS–PLS FCIs worsens significantly with respect to the 08M7–09M6 and 09M7–10M6 out-of-sample intervals. The most prominent case is Thailand, where SRRMSE reaches as high as 3.6 and never falls below 1; Korea and Taiwan are in middle range, which see the predictive power of CSDS–PLS FCIs regain the predictive power as to the 10M7–11M6 out-of-sample interval. The most satisfactory case is Singapore, which sees SRRMSE reaches just over 1 as to the 08M7–09M6 out-of-sample interval and its CSDS–PLS FCIs quickly regain the predictive power at the 09M7–10M6 interval.

In summary, Section 4.5 carries out predictive tests of CSDS–PLS FCIs vs. PLS-R y-predicted and r-predicted FCIs and of CSDS–PLS FCIs vs. benchmark models both pre-2008 crisis and post-2008 crisis. The empirical results generally support the superiority of the CSDS–PLS FCIs against the PLS-R y-predicted and r-predicted FCIs' forecasting model, as well as the benchmark model.

4.6 Empirical results II

This section first investigates the constancy of lag estimates and weight estimates at the disaggregate level across different out-of-sample intervals (Subsection 4.6.1). In the process, more non-constant lags are expected with respect to unstable intervals. Subsection 4.6.2 studies the constancy of the lag estimates and weight estimates across different indicators. Subsection 4.6.3 finally focuses on the predictive power of indicators with respect to the four target economies.

4.6.1 The constancy of lag estimates and weight estimates I

As stated in last section, the forecasting failure of CSDS–PLS FCIs can be explained by the location shift at the aggregate level, which implies non-constant weight estimates at the disaggregate level. The match of location shift and constancy of weight estimates are referred here as the shift-constancy matching pattern for brevity. Furthermore, since the SDS method allows different lags of financial indicators to explain the import price index, the constancy of lag estimates is included as a second criterion to evaluate the constancy at the disaggregate level in addition to that of weight estimates.

From Table 4.7 to Table 4.10, the lag estimates are recorded with respect to different CSDS–PLS factors pre-2008 crisis and post-2008 crisis across the four economies, because different in-sample significant CSDS-PLS factors are observed pre-2008 crisis and post-2008 crisis (according to Table 4.1). In the case of Korea, for example, first and third CSDS–PLS factors are in-sample significant pre-2008 crisis while second and third CSDS–PLS factors become in-sample significant post-2008 crisis. Table 4.7 then records lag estimates with respect to the first and third CSDS–PLS factors pre-2008 crisis and with respect to the second and third CSDS–PLS factors post-2008 crisis.

Table 4.11 summarizes information from Table 4.7 to Table 4.10 by recording the average number of indicators that see their lag estimates shift. In general, the shift-constancy matching postulation is supported. Judging by the average of shift of lags across the four target economies (last row of Table 4.11), there are more shifts of lags with respect to the first 3 out-of-sample intervals (00M7–-03M6). This finding corresponds well to the location shift of CSDS–PLS FCIs pre-2008 crisis. And the number of indicators that see their lag estimates shift reaches the highest during 2008 crisis, namely around 15/35 and 18/35 (07M7–09M6), which also corresponds to the location shift of CSDS–PLS FCIs during the 2008 crisis.

Table 4.17 summarizes information from Table 4.13 to Table 4.16. It records sum squares of weight estimate spread between adjacent updating rounds across the four target economies. The statistics is expressed as follows.

$$ADJ\_W_t^k = \sum_{n=1}^{N}(W_n^t - W_n^{t-1})^2 \quad (4.1)$$

The subscript t refers to the t th out-of-sample interval; the superscript k refers to kth economy; n refers to the nth financial indicator; N refers to the number of financial indicators. Since the in-sample significant CSDS–PLS factors are different pre-2008 crisis and post-2008 crisis, $ADJ\_W_t^k$ is not available between the seventh and eighth round (07M7–08M6 and 08M7–09M6).

The $ADJ\_W_t^k$ statistics also support the shift-constancy matching postulation:

- With respect to the pre-2008 crisis subsample, basically, the shift of weight estimates from the second to the third out-of-sample intervals (01M7–2002M6 to 02M7–03M6) is more moderate than others pre-2008 crisis, especially with respect to Korea and Taiwan.
- With respect to the post-2008 crisis subsample, the shift of weight estimates reaches the highest level from the 9th to 10th out-of-sample interval (08M7–-09M6 and 09M7–-10M6), and large location shifts are observed in these out-of-sample intervals.

4.6.2 The constancy of lag estimates and weight estimates II

From Table 4.12 and Table 4.18, the constancy of financial indicators is evaluated by the shift of lag estimates and weight estimates with respect to each individual indicator. Table 4.12 records the shift of lag estimates, and Table 4.18 records the shift of weight estimates by using $ADJ\_W_n^k$ statistics, that is, sum squares of weight spread between adjacent rounds across out-of-sample intervals.

$$ADJ\_W_n^k = \sum_{t=1}^{T}(W_n^t - W_n^{t-1})^2 \quad (4.2)$$

Because different CSD–PLS factors are observed pre-2008 crisis and post-2008 crisis, $ADJ\_W_n^k$ is divided into

$$ADJ\_W_n^k = \sum_{t=1}^{T^{pre-2008-crisis}}(W_n^t - W_n^{t-1})^2 \quad (4.3)$$

and $\sum_{t=1}^{T^{post-2008-crisis}} (W_n^t - W_n^{t-1})^2$ (4.4)

These two statistics are reported, respectively, as the white and grey columns in Table 18.

Table 4.12 and Table 4.18 show that:

- Derivative indicators are most likely to be constant across the four target economies, and only Korea sees a significant shift of lag estimates.
- Bond–equity yield ratios are second to best: (1) the shift of lag estimates is moderate; and (2) the shift of weight estimates is lower than average.
- By contrast, yield structures of the money market are most susceptible to the 2008 crisis. Judging by $ADJ\_W_n^k$, the shift of their weight estimates is the largest both pre-2008 crisis and post-2008 crisis. To a lesser degree, TED spread also shows considerable shift of weight estimates post-2008 crisis. These results are not very surprising, considering the fact that the short-term interest rates are most sensitive to 2008-crisis.
- Geographically, it seems that Japanese indicators are the most constant, especially among those market misalignment types where US indicators and UK indicators experience a significant shift of weight estimates. TED spread of Japan, for example, has a much smaller scale of shift w.r.t its weight estimate, as compared to that of the UK and US.

In summary, it is notable that a simple removal of the non-constant financial indicators would not result in a stable superior forecasting performance. This is because the indicators that see a significant shift, either of lag estimates or weight estimates during the 2008 crisis, are also likely to contribute significant predictive power in the stable period. For example, yield structures of the money markets are commonly used as barometers to monitor the degree of health of an economy. However, they are among the most non-constant indicators during 2008 crisis.

4.6.3 Leading role of financial indicators

This subsection investigates the leading role of financial indicators mainly from the lag estimates and weight estimates, which are reported, respectively, from Table 4.6 to Table 4.9 and from Table 4.12 to Table 4.15. Indicators' IDs (from X1 to X35) are the same as those in Table 3.1. Table 4.19 summarizes the information from Table 4.6 to 4.9 and from Table 4.12 to Table 4.15. The general findings are as follows.

- Derivative indicators have considerable large weight estimates and provide the most leading information, which is 4-month leading (above the average) with respect to Singapore, Korea, and Taiwan;

- Bond–equity yield ratios and equity–commodity price ratios are among the least leading indicators with respect to Singapore, Korea, and Taiwan, although they are among the most significant indicators;
- Weight estimates of the TED spread and housing–equity price ratios become significant in the post-2008 crisis period.

Since the positive predictive power of CSDS–PLS FCIs is found with respect to those stable, out-of-sample intervals, this subsection only concentrates on the predictive power of indicators with respect to the stable, out-of-sample intervals. Two representative stable, out-of-sample intervals, pre-2008 crisis and post-2008 crisis, respectively, are therefore given higher priority (highlighted as grey columns from Table 4.7 to Table 4.10 and from Table 4.13 to Table 4.16) when evaluating the disaggregate predictive power. Specifically, the weight estimates reported from Table 4.13 and Table 4.16 are rearranged according to their rankings (from highest to lowest) in the two representative intervals. Three blocks that are vertically separated by higher weighted lines are reported from Table 4.13 to Table 4.16.[96] The indicators with positive weight estimates over 0.05 are arranged at the upper block; those indicators with negative weight estimates below -0.05 are arranged at the lower block; and those indicators with insignificant weight estimates between -0.05 and 0.05 are arranged at the middle block.

Singapore

The two representative out-of-sample intervals are the third and eleventh updating rounds (weights updated at 02M6 and 10M6).

Lags: For the lag estimates, From Table 4.7, derivative indicators are above 4r-month leading both the pre-2008 crisis and post-2008 crisis, compared to the less than 3-month leading on average. Yield structures of the money markets are the second best, even though the lag estimates are non-constant across out-of-sample intervals. By contrast, bond–equity yield ratios are least leading of the indicators, with their lags below 2.

Weights: For the weight estimates, from Table 4.13, weight estimates of derivative indicators are more significant (lie in the lower block pre-2008 crisis and post-2008 crisis). Although yield structures of the money market indicators are extremely non-constant (see Subsection 4.6.1 and 4.6.2), they are significant both pre-2008 crisis and post-2008 crisis. Weight estimates of bond–equity yield ratios are significant pre-

[96] Without the selection of two representative out-of-sample intervals, it is impossible to ranked the weight estimates in Table 12-15 and the evaluation of individual indicators are very difficult.

2008-crisis but become insignificant post-2008 crisis (weight estimate of bond–equity yield ratios of Japan is above 0.05, and those of UK and US fall into the middle block). Geographically, Japanese indicators become insignificant post-2008 crisis—only two indicators of Japan—the covered interest parity indicator of Japan and the money–bond interest rate ratios—are below 0.05 pre-2008 crisis, but there are five—bond–equity yield ratios, yield structures of the bond market, TED spread, and money–Inflation rate ratios—that are below 0.05 post-2008 crisis.

Korea

The two representative out-of-sample intervals are fourth and eleventh updating rounds (weights updated at 03M6 and 10M6).[97]

Lags: For the lag estimates, similar results are found in Table 4.8 as those for Singapore. Derivative indicators are around 3-month leading (above the average 2.6); bond–equity yield ratios are around 1-month leading. Contrast findings are also found to be comparable to Singapore. Housing–equity price ratios and market–inflation rate ratios are among the most leading indicators for Korea, while these two types of indicators are average leading for Singapore; indicators measuring yield structures of the money market are only around 1-month leading, compared to over 3-month leading for Singapore.

Weights: For the weight estimates, the comparison between Table 4.14 and Table 4.13 highlights the significant contribution of derivative indicators and yield structures of the money market in the sense that weight estimates of these indicators are significant both pre-2008 crisis and post-2008 crisis. Another finding is that the pre-2008 crisis insignificant TED indicators turn out to be significant post-2008 crisis, while weight estimates of Japanese indicators are significant both pre-2008 crisis and post-2008 crisis.

Taiwan

The two representative out-of-sample intervals are also fourth and eleventh updating rounds (weights updated at 03M6 and 10M6).

Lags: For the lag estimates, similar results are found in Table 4.9 as those in Table 4.8: (1) derivative indicators are leading above the average level (4-month vs. 2.4-month);

[97] It is noteworthy that the first and third CSDS–PLS factors are in-sample significant pre-2008 crisis, while the second and third are in-sample significant post-2008 crisis (see Table 4.1 for the in-sample model specification).

(2) bond–equity yield are below the average level (1-month vs. 2.4-month); (3) market–inflation rate ratios and housing–equity price ratios are leading above the average level but not as obvious as that for Korea; and (4) yield structures of money markets are only around 1-month leading.

Weights: For the weight estimates, from Table 4.15, many findings are different from those in Korean case: (1) two out of three TED spread indicators, TED spread of UK and US, have significant weight estimates both pre-2008 crisis and post-2008 crisis; (2) weight estimate of yield structures of money markets of UK is significant pre-2008 crisis, but it quickly becomes insignificant post-2008 crisis (weight estimate around 0.05 on average); (3) geographically five Japanese indicators—bond–equity yield ratios, covered interest parity indicators, yield structures of the money markets, TED spread, and money–inflation rate ratios—are insignificant pre-2008 crisis but only the TED spread of Japan remains insignificant post-2008 crisis, that is, a trend different from that in Singapore and Korea cases; and (4) money–bond interest ratios are significant both pre-2008 crisis and post-2008 crisis.

Thailand

The two representative out-of-sample intervals are 01M7–02M6 and 12M7–13M6. In general, the lag estimates and weight estimates are quite different from those in the other three economies.

Lags: For the lag estimates, from Table 4.9, the lag estimates are different from those in the other economies in two respects: (1) derivative indicators are not as leading as the other three economies; and (2) although yield structures of the money markets are leading above the average level pre-2008-crisis (similar to the Singapore case), they fall below the average level post-2008 crisis.

Weights: From Table 4.16, the differences are: (1) the insignificant weight estimates of money–bond interest ratios and money–inflation rate ratios both pre-2008 crisis and post-2008 crisis (they are all significant post-2008 crisis with respect to the other economies); and (2) the weight estimates of yield structures of bond markets are significant. Yield structure of bond markest in UK, for example, reaches the highest pre-2008-crisis and yield structures of bond markets from other economies—remain decent high post-2008 crisis, compared to the less significant yield structures of bond market indicators in the above three economies.

In general, the disaggregate findings are different from those in Chapter 3 in that the insignificant bond–equity yield ratios and equity–commodity price ratios (see Chapter 3) now have considerable large weight estimates. In addition, due to the SDS method, the leading role of derivative indicators is highlighted.

4.7 Conclusions

This chapter modifies the construction of PLS-R FCIs in three respects: (1) the FCIs estimated by a Simple Dynamic Sparse revision based on PLS-R, that is, the SDS–PLS method can model the desynchronized disaggregate dynamics; (2) SDS–PLS FCIs are concatenated (CSDS–PLS) and are tested for their predictive power on an annual basis throughout a 13-year (00M7–13M6) out-of-sample period; and (3) the first three CSDS–PLS factors are allowed to enter into the final forecasting model based on the postulation that the first three CSDS–PLS factors may still contain important predictive information, while the first three PLS-R factors may be not all predictive, because the former method can effectively model the desynchronized dynamics while the latter method cannot. In addition to the differences in experimental designs, the empirical findings are listed as follows:

- The superior forecasting performance of CSDS–PLS FCIs vs. the benchmark model is supported for most of the out-of-sample intervals. This finding supports the concatenation method used in constructing FCIs, in terms of predictive power.
- The only exception is Thailand. The forecasting failure of CSDS–PLS FCIs for this target economy strengthens the postulation made in Chapters 2 and Chapter 3 that Thailand has a less open financial sector as compared to the other three developed economies.
- A postulation made in Chapter 3 that the location shift of FCIs caused the forecasting failure during the 2008 crisis is explicitly proved in this chapter, with a modified experimental design that allows the weights, (and, therefore, the aggregate FCIs) to be updated on an annual basis, instead of being fixed for the whole out-of-sample period (see Chapter 3).
- Furthermore, the superiority of the CSDS–PLS FCIs against PLS-R y-predicted and r-predicted FCIs constructed in Chapter 3 is proved here. This is because PLS-R y-predicted and r-predicted FCIs are non-constant. Specifically, by allowing FCIs to be updated on an annual basis, a location shift occurs to CSDS–PLS FCIs at the 00M7–01M6 out-of-sample interval.

In addition to the investigation of weight estimates that has been carried out in Chapter 3, this chapter also focuses on the different leading degrees across financial indicators, estimated by the Simple Dynamic Sparse, and the constancy and leading degrees of financial indicators from the recursively updating of weight estimates and lag estimates. The disaggregate findings are listed as follows:

- First and foremost, the leading degree of the same indicator used in constructing the CSDS–PLS FCIs varies significantly as the target economy varies, in addition to the weight estimate of the same indicator varying with respect to the target economy (Chapter 3). For example, yield structures of the money market are leading above the average with respect to Singapore and Thailand, but among the least leading indicators with respect to Korea and Taiwan. This finding highlights the necessity to use Simple Dynamic Sparse to modify PLS-R in order to differentiate the leading roles of different financial indicators.
- Several findings enhance ones learned in Chapter 3: (1) Chapter 3 found that derivative indicators contribute more than average to the construction of the aggregate PLS-R FCIs. This chapter enhances this finding by showing that the derivative indicators are more constant than other indicators and are leading above the average. The highlighted leading degree of the derivative indicators is due to the fact that the SDS–PLS method can model desynchronized dynamics at the disaggregate level; and (2) Chapter 3 found the TED spread with large weight estimates. This chapter also found significant weight estimates of the TED spread post-2008 crisis, although they are insignificant pre-2008 crisis.
- Contradictory findings were also obtained: (1) weight estimates of bond–equity yield ratios and equity–commodity price ratio turn out be significant, while in Chapter 3, they were found to be much less significant; and (2) housing–equity price ratios are significant post-2008 crisis, with respect to Korea and Taiwan, while in Chapter 3, they were found to be at an average level with respect to these two economies.

Table 4.1 Shift of in-sample significant regressors by 2008 crisis

	Singapore	Korea	Taiwan	Thailand
Macro predictors	$+\Delta X_t^{wp}$	N/A	$+\Delta X_{t-4}^{dp}, -ECM_{t-1}$	$+ECM_{t-1}$
FCIs	$f_{3,t-4}^{SDS}, f_{3,t-6}^{SDS} \rightarrow \Delta_2 f_{1,t}^{SDS}, \Delta_5 f_{1,t}^{SDS}$	$f_{1,t}^{SDS}, f_{3,t}^{SDS}, f_{3,t-5}^{SDS} \rightarrow f_{2,t-1}^{SDS}, \Delta_3 f_{3,t}^{SDS}$	$-\Delta_5 f_{2,t}^{SDS}$	$f_{1,t}^{SDS}, f_{1,t-2}^{SDS} \rightarrow f_{3,t}^{SDS}, f_{3,t-2}^{SDS}$

Table 4.2 CSDS–PLS FCIs vs. PLS-R y-predicted and PLS-R r-predicted FCIs[98]

	SG		KOR		TW		TH	
1-Month	0.955 (0.897)	0.962 (0.841)	0.98 (0.783)	1.01 (0.18)	0.981 (0.839)	1.089 (0.024)	0.931 (0.524)	0.947 (0.423)
2-Months	0.934 (0.946)	0.944 (0.902)	0.98 (0.953)	1.014 (0.096*)	0.978 (0.907)	1.114 (0.054*)	0.949 (0.579)	0.962 (0.488)
3-Months	0.948 (0.877)	0.956 (0.815)	0.970 (0.971)	1.017 (0.044**)	0.97 (0.955)	1.097 (0.116)	0.995 (0.479)	1.013 (0.357)
4-Months	0.967 (0.741)	0.972 (0.683)	0.968 (0.979)	1.022 (0.015**)	0.968 (0.94)	1.056 (0.24)	1.011 (0.4)	1.031 (0.307)
5-Months	0.983 (0.589)	0.986 (0.561)	0.966 (0.959)	1.027 (0.02**)	0.966 (0.888)	1.028 (0.361)	1.027 (0.364)	1.05 (0.281)
6-Months	0.988 (0.526)	0.99 (0.518)	0.964 (0.869)	1.031 (0.184)	0.964 (0.79)	1.023 (0.436)	1.039 (0.371)	1.06 (0.336)

[98] There are two columns of data regarding each target economy. The left column reports the ratio of the rooted mean squared error of CSDS–PLS FCIs vs. PLS-R y-predicted and the p-value of MDM statistics; the right column reports the ratio of the rooted mean squared error of CSDS–PLS FCIs vs. PLS-R r-predicted FCIs and the p-value of MDM statistics.

Table 4.3 Singapore: SDS–PLS FCIs vs. the benchmark model

Out-of-sample period	00M7–01M6	01M7–02M6	02M7–03M6	03M7–04M6	04M7–05M6	05M7–06M6	06M7–07M6	07M7–08M6	08M7–09M6	09M7–10M6	10M7–11M6	11M7–12M6	12M7–13M6
SRRMSE (P-SRRMSE)	1.182	0.959	0.962	0.949	0.963	0.995	0.966	0.938	1.09	1.067	1.051	1.024	0.998
	(.021**)	(0.671)	(0.682)	(0.521)	(0.861)	(0.67)	(0.731)	(0.989)	(.043**)	(.026**)	(0.069*)	(0.14)	(0.475)
	1.204	0.962	0.885	0.774	0.958	0.992	0.964	0.94	1.103	0.992	0.974	0.978	0.943
	(0.04**)	(0.635)	(0.846)	(0.92)	(0.769)	(0.75)	(0.654)	(0.987)	(0.05*)	(0.429)	(0.695)	(0.677)	(0.866)
	1.3	0.974	0.827	0.764	0.949	0.985	0.954	0.934	1.108	0.98	0.949	0.979	0.915
	(.005**)	(0.518)	(0.696)	(0.887)	(0.777)	(0.851)	(0.611)	(0.986)	(.036**)	(0.444)	(0.943)	(0.599)	(0.858)
	1.317	1.004	0.78	0.737	0.933	0.978	0.945	0.928	1.115	0.983	0.943	0.994	0.894
	(0.01**)	(0.381)	(0.635)	(0.88)	(0.878)	(0.918)	(0.563)	(0.984)	(.048**)	(0.452)	(0.943)	(0.48)	(0.772)
	1.327	1.038	0.569	0.751	0.908	0.971	0.947	0.92	1.126	0.919	0.932	0.983	0.909
	(0.067*)	(0.35)	(0.648)	(0.843)	(0.884)	(0.909)	(0.512)	(0.963)	(0.103)	(0.606)	(0.908)	(0.523)	(0.684)
	1.33	1.089	0.566	0.749	0.9	0.967	0.958	0.913	1.135	1.009	0.93	0.984	0.937
	(0.247)	(0.395)	(0.584)	(0.768)	(0.746)	(0.741)	(0.487)	(0.848)	(0.272)	(0.451)	(0.767)	(0.496)	(0.59)
CRRMSE (P-CRRMSE)	1.191	1.013	1.003	0.994	0.988	0.990	0.987	0.977	1.030	1.034	1.034	1.034	1.032
	1.204	1.017	0.992	0.974	0.971	0.978	0.976	0.967	1.043	1.041	1.036	1.031	1.026
	1.300	1.045	1.016	0.987	0.980	0.981	0.978	0.963	1.053	1.051	1.042	1.038	1.033
	1.317	1.078	1.045	1.006	0.990	0.987	0.983	0.962	1.059	1.058	1.046	1.043	1.041
	1.327	1.116	1.076	1.023	1.000	0.991	0.987	0.960	1.065	1.063	1.048	1.046	1.045
	1.330	1.173	1.117	1.042	1.010	0.994	0.991	0.960	1.066	1.065	1.047	1.046	1.045
	0.021	0.189	0.248	0.256	0.333	0.357	0.437	0.730	0.065	0.039	0.027	0.019	0.020
	0.040	0.174	0.286	0.414	0.497	0.547	0.606	0.889	0.061	0.059	0.066	0.073	0.088
	0.005	0.076	0.129	0.252	0.339	0.408	0.454	0.865	0.034	0.033	0.045	0.048	0.059
	0.010	0.045	0.069	0.160	0.246	0.310	0.338	0.825	0.028	0.028	0.040	0.040	0.044
	0.067	0.044	0.052	0.123	0.199	0.272	0.281	0.789	0.032	0.032	0.050	0.050	0.051
	0.247	0.041	0.044	0.111	0.180	0.266	0.256	0.762	0.043	0.041	0.065	0.064	0.065

Table 4.4 Korea: SDS–PLS FCIs vs. benchmark model

Out-of-sample period	00M7–01M6	01M7–02M6	02M7–03M6	03M7–04M6	04M7–05M6	05M7–06M6	06M7–07M6	07M7–08M6	08M7–09M6	09M7–10M6	10M7–11M6	11M7–12M6	12M7–13M6
SRRMSE (P-SRRMSE)	0.969 (0.203)	0.881 (0.578)	0.994 (0.237)	0.957 (0.245)	0.914 (0.943)	0.97 (0.55)	0.983 (0.418)	1.347 (.013**)	1.188 (0.1)	0.94 (0.936)	0.796 (0.988)	1.105 (0.094*)	1.064 (0.127)
	1.196 (0.085*)	0.877 (0.578)	1.093 (0.101)	0.787 (0.178)	1.004 (0.343)	0.98 (0.482)	1.045 (0.201)	1.378 (.022**)	1.271 (0.077*)	0.982 (0.61)	0.795 (0.98)	1.166 (0.085*)	1.12 (0.098*)
	1.476 (.027**)	0.839 (0.674)	1.221 (.041**)	0.49 (0.299)	1.067 (0.182)	0.983 (0.443)	1.057 (0.188)	1.374 (.046**)	1.348 (0.068*)	0.974 (0.631)	0.77 (0.993)	1.182 (0.122)	1.185 (0.085*)
	1.638 (.025**)	0.805 (0.776)	1.366 (0.056*)	0.4 (0.442)	1.036 (0.317)	0.952 (0.491)	1.027 (0.267)	1.365 (0.089*)	1.407 (0.078*)	0.977 (0.632)	0.759 (0.998)	1.225 (0.168)	1.474 (0.052*)
	1.694 (.048**)	0.817 (0.668)	1.83 (0.119)	0.373 (0.502)	1.091 (0.249)	0.918 (0.561)	0.977 (0.421)	1.354 (0.163)	1.47 (0.124)	0.981 (0.642)	0.761 (0.998)	1.251 (0.234)	1.778 (0.086*)
	1.681 (0.145)	0.851 (0.545)	2.154 (0.281)	0.307 (0.566)	1.073 (0.374)	0.881 (0.576)	0.969 (0.465)	1.355 (0.306)	1.527 (0.283)	0.989 (0.524)	0.767 (0.96)	1.594 (0.285)	1.767 (0.261)
CRRMSE (P-CRRMSE)	0.957 (0.203)	0.922 (0.295)	0.96 (0.173)	0.953 (0.114)	0.942 (0.308)	0.944 (0.329)	0.95 (0.313)	1.009 (.025**)	1.065 (.024**)	1.055 (.028**)	1.044 (.035**)	1.044 (.025**)	1.049 (.019**)
	1.196 (0.085*)	1.017 (0.124)	1.056 (0.03**)	1.028 (.016**)	1.021 (.014**)	1.012 (.016**)	1.016 (0.01**)	1.101 (.001**)	1.175 (.006**)	1.164 (.006**)	1.143 (.007**)	1.145 (.005**)	1.144 (.003**)
	1.476 (.027**)	1.075 (0.067*)	1.144 (.005**)	1.073 (.003**)	1.071 (.001**)	1.054 (.002**)	1.054 (.001**)	1.153 (.001**)	1.25 (.003**)	1.24 (.003**)	1.208 (.004**)	1.206 (.003**)	1.206 (.002**)
	1.638 (.025**)	1.117 (0.063*)	1.21 (.004**)	1.095 (.004**)	1.074 (.002**)	1.058 (.003**)	1.054 (.002**)	1.164 (.001**)	1.292 (.003**)	1.28 (.003**)	1.24 (.004**)	1.239 (.003**)	1.244 (.002**)
	1.694 (.048**)	1.171 (0.067*)	1.313 (.005**)	1.135 (.005**)	1.121 (.002**)	1.087 (.002**)	1.075 (.002**)	1.185 (.001**)	1.339 (.003**)	1.326 (.003**)	1.274 (.004**)	1.273 (.003**)	1.28 (.002**)
	1.681 (0.145)	1.291 (0.059*)	1.454 (.004**)	1.178 (.006**)	1.14 (.002**)	1.092 (.004**)	1.082 (.003**)	1.189 (.001**)	1.363 (.004**)	1.346 (.004**)	1.284 (.006**)	1.286 (.004**)	1.292 (.003**)

Table 4.5 Taiwan: SDS–PLS FCIs vs. benchmark model

	00M7–01M6	01M7–02M6	02M7–03M6	03M7–04M6	04M7–05M6	05M7–06M6	06M7–07M6	07M7–08M6	08M7–09M6	09M7–10M6	10M7–11M6	11M7–12M6	12M7–13M6
SRRMSE (P-SRRMSE)	1.064 (0.123)	0.964 (0.641)	1.137 (0.065*)	0.737 (0.698)	0.872 (0.553)	0.844 (0.861)	0.966 (0.625)	1.266 (.032**)	1.067 (.115)	1.131 (.039**)	0.901 (0.735)	1.142 (0.052*)	0.97 (0.611)
	0.961 (0.388)	0.958 (0.686)	1.231 (.047**)	0.627 (0.812)	0.822 (0.525)	0.797 (0.897)	0.963 (0.547)	1.37 (.031**)	1.081 (0.119)	1.161 (.028**)	0.851 (0.823)	1.14 (.041**)	0.983 (0.529)
	0.802 (0.583)	0.964 (0.66)	1.366 (0.04**)	0.519 (0.884)	0.747 (0.566)	0.745 (0.904)	0.968 (0.481)	1.344 (0.061*)	1.107 (0.111)	1.287 (.009**)	0.802 (0.909)	1.162 (0.073*)	1.027 (0.224)
	0.725 (0.649)	0.975 (0.583)	1.599 (.048**)	0.5 (0.908)	0.679 (0.561)	0.689 (0.86)	0.942 (0.516)	1.344 (0.112)	1.163 (0.115)	1.288 (0.03**)	0.772 (0.948)	1.226 (0.093*)	1.11 (0.073*)
	0.687 (0.649)	0.982 (0.535)	1.903 (0.081*)	0.489 (0.913)	0.609 (0.459)	0.677 (0.771)	0.923 (0.516)	1.336 (0.184)	1.218 (0.184)	1.291 (0.053*)	0.765 (0.973)	1.347 (0.118)	1.179 (0.103)
	0.63 (0.631)	1.009 (0.469)	2.345 (0.191)	0.485 (0.816)	0.379 (0.505)	0.657 (0.654)	0.915 (0.498)	1.362 (0.32)	1.262 (0.341)	1.347 (0.218)	0.776 (0.987)	1.54 (0.198)	1.181 (0.304)
CRRMSE (P-CRRMSE)	1.064 (0.123)	0.964 (0.641)	1.137 (0.065*)	0.737 (0.698)	0.872 (0.553)	0.844 (0.861)	0.966 (0.625)	1.266 (.032**)	1.067 (0.115)	1.131 (.039**)	0.901 (0.735)	1.142 (0.052*)	0.97 (0.611)
	0.961 (0.388)	0.958 (0.686)	1.231 (.047**)	0.627 (0.812)	0.822 (0.525)	0.797 (0.897)	0.963 (0.547)	1.37 (.031**)	1.081 (0.119)	1.161 (.028**)	0.851 (0.823)	1.14 (.041**)	0.983 (0.529)
	0.802 (0.583)	0.964 (0.66)	1.366 (0.04**)	0.519 (0.884)	0.747 (0.566)	0.745 (0.904)	0.968 (0.481)	1.344 (0.061*)	1.107 (0.111)	1.287 (.009**)	0.802 (0.909)	1.162 (0.073*)	1.027 (0.224)
	0.725 (0.649)	0.975 (0.583)	1.599 (.048**)	0.5 (0.908)	0.679 (0.561)	0.689 (0.86)	0.942 (0.516)	1.344 (0.112)	1.163 (0.115)	1.288 (0.03**)	0.772 (0.948)	1.226 (0.093*)	1.11 (0.073*)
	0.687 (0.649)	0.982 (0.535)	1.903 (0.081*)	0.489 (0.913)	0.609 (0.459)	0.677 (0.771)	0.923 (0.516)	1.336 (0.184)	1.218 (0.184)	1.291 (0.053*)	0.765 (0.973)	1.347 (0.118)	1.179 (0.103)
	0.63 (0.631)	1.009 (0.469)	2.345 (0.191)	0.485 (0.816)	0.379 (0.505)	0.657 (0.654)	0.915 (0.498)	1.362 (0.32)	1.262 (0.341)	1.347 (0.218)	0.776 (0.987)	1.54 (0.198)	1.181 (0.304)

Table 4.6 Thailand: SDS–PLS FCIs vs. benchmark model

	00M7–01M6	01M7–02M6	02M7–03M6	03M7–04M6	04M7–05M6	05M7–06M6	06M7–07M6	07M7–08M6	08M7–09M6	09M7–10M6	10M7–11M6	11M7–12M6	12M7–13M6
SRRMSE (P-SRRMSE)	0.836 (0.321)	0.728 (0.564)	0.895 (0.477)	0.994 (0.081*)	0.954 (0.258)	1.215 (.014**)	1.318 (.006**)	1.821 (.002**)	2.578 (.016**)	1.375 (0.109)	1.254 (.041**)	0.964 (0.077*)	0.676 (.013**)
	1.066 (0.114)	0.984 (0.212)	1.149 (0.06*)	1.097 (.049**)	0.968 (0.353)	1.253 (.008**)	1.434 (.012**)	1.886 (.001**)	2.83 (0.03**)	1.597 (0.051*)	1.367 (0.054*)	1.264 (0.08*)	1.163 (.001**)
	1.308 (0.096*)	0.88 (0.259)	1.136 (0.116)	1.278 (0.054*)	1.002 (0.327)	1.25 (.013**)	1.497 (.019**)	1.958 (.001**)	3.079 (.041**)	1.506 (0.08*)	1.433 (0.053*)	1.766 (0.051*)	1.37 (.001**)
	1.468 (0.121)	0.589 (0.281)	0.935 (0.296)	1.417 (0.108)	1.002 (0.421)	1.191 (.031**)	1.6 (.026**)	1.955 (.002**)	3.336 (0.06*)	1.423 (0.144)	1.435 (0.065*)	1.906 (.041**)	1.659 (.002**)
	1.619 (0.175)	0.72 (0.27)	0.84 (0.405)	1.31 (0.212)	0.959 (0.568)	1.107 (0.218)	1.605 (0.078*)	1.958 (.008**)	3.475 (0.107)	1.43 (0.223)	1.433 (0.084*)	2.172 (0.064*)	1.625 (.006**)
	1.477 (0.297)	0.778 (0.308)	0.675 (0.493)	0.922 (0.37)	0.922 (0.617)	1.001 (0.466)	1.606 (0.257)	1.954 (0.083*)	3.601 (0.253)	1.446 (0.355)	1.391 (0.261)	3.876 (0.175)	1.894 (0.092*)
CRRMSE (P-CRRMSE)	0.849 (0.321)	0.804 (0.402)	0.855 (0.426)	0.88 (0.162)	0.883 (0.15)	0.938 (.043**)	0.997 (.006**)	1.185 (.001**)	1.525 (.002**)	1.517 (.002**)	1.503 (.001**)	1.492 (.001**)	1.476 (.001**)
	1.066 (0.114)	1.042 (0.058*)	1.098 (.009**)	1.098 (.001**)	1.085 (.001**)	1.139 (.001**)	1.197 (.001**)	1.435 (.001**)	1.902 (.003**)	1.893 (.002**)	1.85 (.002**)	1.84 (.001**)	1.831 (.001**)
	1.308 (0.096*)	1.167 (.045**)	1.149 (.012**)	1.185 (.001**)	1.158 (.001**)	1.191 (.001**)	1.254 (.001**)	1.566 (.001**)	2.114 (.003**)	2.097 (.002**)	2.034 (.002**)	2.031 (.001**)	2.023 (.001**)
	1.468 (0.121)	1.261 (0.056*)	1.066 (0.04**)	1.154 (.007**)	1.126 (.006**)	1.147 (.001**)	1.229 (.001**)	1.613 (.001**)	2.237 (.003**)	2.213 (.002**)	2.13 (.002**)	2.128 (.002**)	2.123 (.001**)
	1.619 (0.175)	1.41 (0.056*)	1.075 (0.058*)	1.142 (.014**)	1.105 (.014**)	1.105 (.006**)	1.188 (.001**)	1.64 (.001**)	2.289 (.003**)	2.26 (.003**)	2.167 (.002**)	2.167 (.002**)	2.16 (.001**)
	1.477 (0.297)	1.353 (0.052*)	0.984 (0.09*)	0.967 (.031**)	0.957 (.032**)	0.969 (.026**)	1.056 (.004**)	1.616 (.003**)	2.261 (.003**)	2.233 (.003**)	2.129 (.002**)	2.134 (.002**)	2.132 (.002**)

Table 4.7 Singapore: Lag structure of the in-sample significant factor

	3rd factor									1st factor			
ID[99]	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	09M6	10M6	11M6	12M6
X1	2	2	2	2	2	2	2	1	2	1	1	1	1
X2	1	5	1	1	1	1	1	6	6	1	1	5	1
X3	2	2	2	2	2	2	2	6	6	1	6	6	6
X4	3	6	1	1	1	1	1	6	3	3	3	3	3
X5	2	2	2	2	2	2	2	6	6	3	3	3	3
X6	1	1	1	1	1	1	1	1	1	1	1	1	1
X7	1	1	3	3	3	3	3	1	4	1	1	1	1
X8	1	1	1	2	5	5	2	1	6	6	6	1	6
X9	6	2	6	6	6	6	6	6	6	6	6	2	2
X10	1	1	1	1	1	1	1	1	6	1	1	6	1
X11	2	2	2	2	2	2	2	2	2	2	2	2	2
X12	4	1	1	1	1	1	1	1	1	3	3	3	5
X13	6	5	1	4	3	1	1	4	2	2	2	2	2
X14	6	5	5	1	5	5	1	1	6	6	6	6	6
X15	6	6	6	6	6	6	2	6	6	6	6	6	6
X16	6	6	2	1	1	1	1	1	1	4	4	4	4
X17	2	3	1	1	1	1	1	1	2	1	1	1	1
X18	3	3	3	3	3	3	6	3	3	3	3	3	3
X19	4	4	4	1	4	1	1	1	2	1	1	1	1
X20	1	1	1	1	1	1	2	2	5	1	1	1	1
X21	2	6	6	2	2	6	2	6	6	1	1	1	1
X22	2	2	2	2	2	2	2	2	6	2	2	2	2
X23	1	1	1	1	3	1	1	1	3	1	1	1	1
X24	6	2	2	2	2	6	2	2	2	2	1	1	1
X25	4	3	1	1	1	1	1	6	3	1	1	1	1
X26	4	4	6	6	6	6	6	6	6	6	6	6	6
X27	4	4	4	4	4	4	4	4	4	4	4	4	4
X28	2	2	6	3	6	3	3	3	3	4	4	4	4
X29	2	2	1	1	1	1	1	6	6	1	1	1	1
X30	3	3	3	3	3	3	6	2	2	3	3	3	3
X31	1	1	3	3	3	3	4	5	5	6	5	5	5
X32	1	1	1	5	5	5	6	1	1	1	1	1	2
X33	1	2	6	2	2	2	2	4	6	4	4	4	4
X34	6	1	1	1	5	5	1	4	6	6	6	3	3
X35	1	1	1	1	1	1	1	5	5	4	4	4	4
Ave	2.85	2.68	2.57	2.25	2.77	2.71	2.31	3.25	4	2.82	2.91	2.82	2.8

[99] X1 to X35 are indicators ID, which are defined in Table 3.1.

Table 4.8 Korea: Lag structure of the in-sample significant factor

	1st Factor									2nd Factor			
	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	09M6	10M6	11M6	12M6
X1	1	1	1	1	1	1	1	1	1	1	1	1	1
X2	2	1	1	1	1	1	1	1	1	1	1	1	1
X3	2	2	2	2	2	2	2	2	2	1	1	1	1
X4	1	1	1	1	1	1	1	1	6	2	6	6	6
X5	1	1	1	1	1	1	1	1	3	4	4	4	4
X6	1	1	1	1	1	1	1	1	1	1	1	1	1
X7	5	5	3	3	2	2	2	2	2	1	1	1	1
X8	5	5	2	2	2	1	2	2	4	1	1	1	1
X9	6	1	2	2	3	6	6	6	6	6	6	1	6
X10	1	1	1	1	1	1	1	1	1	1	1	1	1
X11	1	1	2	2	2	2	2	2	1	3	3	3	3
X12	1	1	1	1	1	1	1	1	1	1	1	1	1
X13	3	3	3	3	3	3	3	3	3	6	6	6	2
X14	1	1	1	1	1	1	1	1	1	1	1	1	1
X15	1	1	1	1	1	1	1	4	4	1	1	1	1
X16	1	1	1	1	1	1	1	1	1	4	4	4	4
X17	3	1	5	5	4	4	4	2	6	2	2	2	2
X18	4	4	5	5	3	3	3	3	2	2	2	2	2
X19	4	4	4	4	1	6	1	1	1	1	1	1	1
X20	1	1	1	1	1	1	1	1	1	1	1	1	1
X21	3	3	3	6	1	1	1	6	6	1	1	1	1
X22	2	2	2	2	2	2	2	2	6	2	2	2	2
X23	1	1	1	1	1	1	6	6	6	3	6	3	1
X24	2	2	2	2	2	2	2	2	3	2	2	2	1
X25	5	4	5	6	6	6	1	1	3	1	1	1	1
X26	4	4	4	4	4	4	4	4	4	4	4	4	4
X27	4	4	4	4	4	4	4	4	4	4	4	4	4
X28	3	4	4	4	4	4	4	4	4	4	4	4	4
X29	1	1	1	1	1	1	1	1	1	3	3	3	3
X30	6	6	6	6	1	1	1	1	1	1	1	1	1
X31	1	1	1	3	2	2	2	2	6	1	1	1	6
X32	1	1	4	2	1	5	5	5	4	4	4	4	4
X33	6	2	2	2	2	2	2	2	2	1	1	1	1
X34	6	6	1	1	1	5	5	5	1	6	3	6	1
X35	1	1	1	1	1	1	5	5	6	5	5	5	4

	3rd Factor									3rd Factor			
X1	2	2	1	1	1	1	1	1	1	1	1	1	1
X2	1	1	1	1	1	1	1	1	1	1	1	1	1
X3	2	2	1	1	1	2	1	1	1	1	1	1	1
X4	6	6	6	1	6	1	1	1	1	6	6	6	6
X5	1	1	1	1	1	1	1	1	4	4	4	4	4
X6	1	1	1	1	1	1	1	1	1	1	1	1	1
X7	1	2	2	2	2	2	1	2	2	1	1	1	1
X8	2	5	1	1	1	1	1	1	1	1	1	1	1
X9	6	6	6	6	6	6	6	2	2	6	6	6	2
X10	1	1	1	1	1	1	1	1	1	1	1	1	1
X11	1	1	1	2	2	2	2	2	2	6	6	6	2
X12	5	4	1	1	1	1	1	1	1	1	1	1	1
X13	6	1	1	1	1	1	1	1	1	6	6	1	1
X14	1	1	3	3	3	3	3	4	4	4	4	4	4
X15	1	1	1	6	6	1	1	6	2	1	1	1	1
X16	1	1	1	1	1	1	1	1	3	1	1	1	1
X17	6	1	1	1	1	1	1	1	1	5	5	5	5
X18	5	3	4	3	4	4	4	4	3	5	5	2	6
X19	4	1	4	4	4	1	2	1	2	4	4	1	4
X20	1	1	1	1	1	1	1	1	2	1	1	1	1
X21	6	6	6	6	6	6	6	6	6	1	1	1	1
X22	1	1	2	2	2	2	2	2	2	2	1	1	1
X23	1	1	1	1	1	1	1	1	1	1	1	1	1
X24	1	1	1	2	2	1	1	1	1	1	1	1	1
X25	2	2	3	6	6	6	1	1	2	1	1	1	1
X26	1	4	4	4	6	6	6	6	6	4	4	4	4
X27	1	1	1	1	1	6	6	1	6	1	1	1	1
X28	6	6	1	1	1	1	1	1	1	6	6	6	6
X29	3	4	4	3	3	4	6	3	6	3	3	3	3
X30	1	1	2	2	1	1	1	1	1	1	1	1	1
X31	4	1	6	5	5	1	1	1	1	6	6	6	6
X32	6	6	6	5	5	6	2	2	2	1	1	1	1
X33	6	6	1	5	5	1	1	1	1	1	1	1	6
X34	1	1	1	1	1	1	5	5	6	5	5	5	4
X35	1	1	3	2	3	3	3	3	2	6	6	6	2
Ave	2.40	2.31	2.71	2.57	2.71	2.96	2.80	2.19	2.56	2.77	2.64	2.46	2.29

Table 4.9 Taiwan: Lag structure of the in-sample significant factor

	2nd factor									2nd factor			
ID	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	09M6	10M6	11M6	12M6
X1	1	1	1	1	1	1	1	1	1	1	1	1	1
X2	2	1	1	1	1	1	1	1	1	1	1	1	1
X3	2	2	2	2	2	2	2	2	2	1	1	1	1
X4	1	1	1	1	1	1	1	1	6	2	6	6	6
X5	1	1	1	1	1	1	1	1	3	4	4	4	4
X6	1	1	1	1	1	1	1	1	1	1	1	1	1
X7	5	5	3	3	2	2	2	2	2	1	1	1	1
X8	5	5	2	2	2	1	2	2	4	1	1	1	1
X9	6	1	2	2	3	6	6	6	6	6	6	1	6
X10	1	1	1	1	1	1	1	1	1	1	1	1	1
X11	1	1	2	2	2	2	2	2	1	3	3	3	3
X12	1	1	1	1	1	1	1	1	1	1	1	1	1
X13	1	1	1	1	1	1	1	1	1	1	1	1	1
X14	3	4	4	4	4	4	4	4	4	4	4	4	4
X15	1	1	1	1	1	1	1	1	1	1	1	1	1
X16	1	1	1	1	1	1	1	4	4	1	1	1	1
X17	1	1	1	1	1	1	1	1	1	4	4	4	4
X18	3	1	5	5	4	4	4	2	6	2	2	2	2
X19	4	4	5	5	3	3	3	3	2	2	2	2	2
X20	4	4	4	4	1	6	1	1	1	1	1	1	1
X21	3	3	3	6	1	1	1	6	6	1	1	1	1
X22	2	2	2	2	2	2	2	2	6	2	2	2	2
X23	1	1	1	1	1	1	6	6	6	3	6	3	1
X24	2	2	2	2	2	2	2	2	3	2	2	2	1
X25	5	4	5	6	6	6	1	1	3	1	1	1	1
X26	4	4	4	4	4	4	4	4	4	4	4	4	4
X27	4	4	4	4	4	4	4	4	4	4	4	4	4
X28	1	1	1	1	1	1	1	1	1	3	3	3	3
X29	6	6	6	6	1	1	1	1	1	1	1	1	1
X30	1	1	1	3	2	2	2	2	6	1	1	1	6
X31	1	1	4	2	1	5	5	5	4	4	4	4	4
X32	6	2	2	2	2	2	2	2	2	1	1	1	1
X33	6	6	1	1	1	5	5	5	1	6	3	6	1
X34	1	1	1	1	1	1	5	5	6	5	5	5	4
X35	3	3	3	3	3	3	3	3	3	6	6	6	2
Ave	2.60	2.26	2.29	2.40	1.89	2.31	2.31	2.49	3.00	2.37	2.49	2.34	2.26

Table 4.10 Thailand: Lag structure of the in-sample significant factor

	1st factor									3rd factor			
ID	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	09M6	10M6	11M6	12M6
X1	2	2	2	2	2	2	2	2	6	4	4	2	2
X2	1	1	1	1	1	1	1	1	1	1	1	1	1
X3	2	2	2	2	2	6	6	1	2	2	2	2	1
X4	1	1	1	1	1	1	1	1	1	6	6	6	6
X5	4	1	1	1	4	1	1	1	6	6	6	6	6
X6	1	1	1	1	1	1	1	1	1	1	1	1	1
X7	1	1	1	1	1	1	1	1	5	5	5	2	2
X8	2	2	2	3	3	3	3	5	3	6	6	6	6
X9	2	2	2	2	2	2	2	6	2	6	6	2	2
X10	1	1	1	1	1	1	1	1	1	1	1	1	1
X11	1	1	1	1	1	1	1	1	1	1	1	1	1
X12	4	4	4	4	6	6	6	3	6	6	6	6	1
X13	6	6	6	6	6	6	6	1	2	6	6	5	6
X14	1	1	1	1	1	1	1	1	1	1	1	1	1
X15	6	6	6	6	6	6	6	6	2	2	6	6	2
X16	2	2	2	2	2	2	2	3	2	1	1	1	1
X17	2	1	1	1	1	1	1	1	4	4	3	3	3
X18	1	1	1	1	1	1	2	1	2	1	1	1	1
X19	4	4	4	4	4	4	4	1	1	1	1	1	1
X20	1	1	1	1	1	1	1	1	1	6	6	6	6
X21	2	2	2	2	5	1	1	6	6	1	1	1	1
X22	2	2	4	4	4	4	4	4	1	2	1	1	1
X23	1	1	1	1	1	1	1	1	1	1	1	1	1
X24	1	1	1	1	1	4	4	1	1	1	1	1	1
X25	5	5	6	6	5	6	6	1	6	6	6	6	6
X26	1	1	1	1	1	1	1	1	1	1	1	1	1
X27	4	4	4	4	4	4	4	4	4	4	4	4	4
X28	4	4	4	4	4	4	4	4	4	4	4	4	4
X29	1	1	1	1	1	1	1	1	6	6	6	6	6
X30	4	4	4	4	4	6	6	1	1	4	1	1	1
X31	1	1	1	6	6	6	6	1	5	3	3	3	3
X32	2	2	6	6	6	4	4	4	3	3	3	3	3
X33	1	6	3	3	4	4	4	2	3	1	4	4	4
X34	5	2	2	2	2	2	2	3	5	5	5	5	5
X35	6	6	6	6	6	6	6	6	2	6	2	6	6
Ave	2.43	2.37	2.49	2.66	2.89	2.91	2.94	2.26	2.83	3.29	3.23	3.06	2.80

Table 4.11 Number of indicators seeing estimated lag shifts

Adjacent round	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	N/A	10-11	11-12	12-13
SG	12	13	9	7	6	11	19	15	N/A	3	5	5
KOR	11.5	13.5	10.5	7	10	8.5	10	13	N/A	1.5	2	5.5
TW	6	9	4	9	5	5	3	13	N/A	3	3	7
TH	4	4	2	5	7	1	14	20	N/A	6	5	4
AVE	8.375	9.875	6.375	7	7	6.375	11.75	15.25	N/A	3.375	3.75	5.375

Table 4.12 Number of intervals seeing estimated lag shifts

ID	SG	TH	KOR	TW	AVE	ID	SG	TH	KOR	TW	AVE
X1	3	3	2	0	1.875	X20	3	4	3	0	2.375
X2	6	0	1	1	2	X21	6	4	3	4	4.25
X3	3	4	3	1	2.75	X22	2	4	2	2	2.375
X4	4	1	4	3	2.875	X23	4	0	1	5	2.5
X5	2	4	2	2	2.5	X24	4	2	2	3	2.75
X6	0	0	1	0	0.25	X25	5	5	5	6	5.125
X7	4	2	5	3	3.5	X26	1	0	3	0	0.875
X8	7	4	3	5	4.75	X27	0	0	5	0	1.125
X9	3	4	4	6	4.25	X28	5	0	5	0	2.5
X10	4	0	0	0	1	X29	5	0	3	1	2.125
X11	0	0	3	3	1.5	X30	3	1	3	1	2
X12	3	4	3	0	2.375	X31	3	4	5	1	3.125
X13	3	4	3	0	5.125	X32	5	4	4	5	4.375
X14	5	0	5	0	2.5	X33	4	3	6	5	4.5
X15	5	0	5	0	2	X34	6	7	4	2	4.75
X16	2	3	1	2	2.125	X35	6	3	7	7	5.625
X17	3	3	2	1	5.25						
X18	4	3	8	6	4						
X19	2	4	7	3	2.75						

Table 4.13 Singapore: Ranking financial indicators by weights updated at 02M6 and 09M6

3rd factor										1st factor				
ID	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	ID	09M6	10M6	11M6	12M6
X3	0.141	0.186	0.266	0.347	0.323	0.133	0.206	0.118	0.085	x20	0.125	0.134	0.043	0.075
X6	0.009	0.077	0.217	0.286	0.277	0.134	0.226	0.056	0.075	x19	0.107	0.108	0.086	0.103
x33	-0.039	0.130	0.191	0.176	0.169	0.101	0.012	0.107	0.126	x27	0.112	0.105	0.106	0.125
X2	-0.108	-0.150	0.177	0.275	0.248	0.062	0.146	0.081	0.035	x35	0.096	0.097	0.099	0.108
x18	0.120	0.138	0.167	0.201	0.220	0.139	-0.094	-0.031	-0.013	x22	0.061	0.081	0.116	0.032
x21	-0.231	0.145	0.162	-0.228	-0.214	0.176	-0.186	0.120	0.078	x24	0.079	0.074	0.083	0.083
x29	0.066	0.042	0.139	0.141	0.118	0.049	0.082	0.068	0.049	x26	0.072	0.069	0.055	0.064
x35	0.120	0.107	0.130	0.136	0.110	0.051	0.001	0.067	0.095	x28	0.067	0.065	0.078	0.074
X1	0.078	0.080	0.129	0.182	0.196	0.079	0.044	0.108	0.064	x16	0.060	0.054	0.066	0.073
x16	-0.311	-0.322	0.118	0.200	0.192	0.007	0.157	0.047	0.010	x15	0.049	0.052	0.012	0.028
X10	0.060	0.096	0.111	0.164	0.196	0.142	0.168	0.048	0.028	x33	0.051	0.047	0.030	0.041
x30	0.078	0.066	0.103	0.136	0.158	0.070	-0.080	-0.092	-0.094	x25	0.040	0.047	-0.075	0.030
x25	0.059	-0.046	0.079	0.064	0.055	0.053	0.079	0.056	0.121	x29	0.047	0.046	0.020	0.027
X7	-0.023	-0.012	0.077	0.107	0.095	0.083	0.189	0.043	0.029	X5	0.041	0.040	0.017	0.028
X11	0.019	0.051	0.072	0.149	0.153	0.068	0.155	0.020	-0.110	X9	0.030	0.035	-0.071	0.013
x32	0.047	0.040	0.051	0.083	0.102	0.049	-0.050	-0.004	0.036	x23	0.026	0.022	-0.006	0.023
x28	-0.022	-0.050	0.041	-0.060	0.049	-0.035	-0.198	-0.032	0.029	x34	0.007	0.012	0.003	0.000
x17	0.030	-0.085	0.018	0.036	0.055	0.062	0.036	-0.126	-0.150	X3	-0.103	0.008	-0.106	-0.085
x34	0.072	0.003	0.008	0.003	-0.065	-0.060	0.094	-0.010	0.053	X7	0.004	0.003	-0.032	-0.016
X8	-0.033	-0.022	-0.005	0.024	-0.034	-0.019	0.144	-0.019	0.033	X8	-0.033	-0.035	-0.024	-0.033
x20	-0.177	-0.122	-0.010	-0.011	-0.018	-0.064	-0.052	-0.059	-0.084	X10	-0.039	-0.040	0.030	0.031

x23	-0.046	-0.081	-0.023	-0.015	0.149	-0.052	-0.168	0.067	0.038	x30	-0.050	-0.046	-0.052	-0.056
X4	0.040	0.048	-0.033	-0.028	-0.011	-0.027	-0.112	-0.127	-0.087	x21	-0.065	-0.061	-0.085	-0.075
x13	-0.047	0.087	-0.034	0.104	0.104	-0.035	-0.051	-0.106	-0.047	x18	-0.077	-0.075	-0.093	-0.087
x24	0.184	-0.030	-0.041	-0.112	-0.109	0.222	-0.124	-0.078	-0.104	X2	-0.095	-0.086	-0.079	-0.088
x19	-0.143	-0.118	-0.057	-0.047	-0.016	-0.055	-0.162	-0.101	-0.052	X1	-0.083	-0.095	-0.040	-0.058
X9	-0.112	0.033	-0.070	-0.116	-0.140	-0.076	-0.041	0.048	0.084	x13	-0.082	-0.096	-0.057	-0.084
x31	0.061	0.026	-0.093	-0.123	-0.115	-0.061	-0.026	-0.072	-0.060	x14	-0.094	-0.098	-0.108	-0.099
X5	-0.054	-0.064	-0.107	-0.149	-0.124	-0.079	-0.255	-0.117	-0.142	x32	-0.106	-0.101	-0.102	-0.104
x14	0.197	-0.120	-0.137	0.013	-0.133	-0.138	0.099	-0.089	-0.019	X4	-0.116	-0.133	-0.124	-0.127
x15	-0.161	-0.161	-0.155	-0.200	-0.224	-0.188	0.260	-0.079	0.027	x12	-0.125	-0.137	-0.126	-0.120
x26	-0.191	-0.204	-0.168	-0.145	-0.120	-0.139	-0.190	-0.132	-0.143	X11	-0.141	-0.142	-0.135	-0.131
x12	-0.086	-0.113	-0.192	-0.271	-0.264	-0.128	-0.269	-0.154	-0.164	x31	-0.154	-0.148	-0.131	-0.143
x22	-0.071	-0.198	-0.194	-0.220	-0.168	-0.142	-0.278	-0.047	0.034	X6	-0.172	-0.166	-0.129	-0.164
x27	-0.140	-0.156	-0.213	-0.253	-0.236	-0.149	-0.254	-0.101	0.054	x17	-0.214	-0.203	-0.168	-0.199

Table 4.14 Korea: Ranking financial indicators by weight estimates updated at 03M6 and 10M6

First factor										Second factor				
ID	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	ID	09M6	10M6	11M6	12M6
x13	0.124	0.163	0.166	0.166	0.15	0.134	0.113	0.200	0.208	X6	0.251	0.238	0.243	0.202
X11	0.124	0.146	0.138	0.145	0.106	0.073	0.063	0.177	0.080	X2	0.227	0.218	0.205	0.227
x16	0.104	0.115	0.105	0.112	0.081	0.063	0.054	0.179	0.045	X3	0.186	0.177	0.163	0.188
X4	0.051	0.086	0.096	0.106	0.094	0.088	0.081	0.145	0.199	x21	0.142	0.158	0.148	0.161
X3	0.147	0.125	0.122	0.099	0.025	-0.101	-0.107	0.019	-0.007	x17	0.122	0.140	0.117	0.167
X2	0.172	0.149	0.141	0.082	0.008	-0.109	-0.114	0.140	0.086	X10	0.117	0.116	0.103	0.122
X10	0.074	0.099	0.1	0.08	0.032	0.012	0.008	0.113	0.080	X1	0.118	0.113	0.107	0.103
X6	0.122	0.132	0.113	0.073	0.012	-0.072	0.001	0.053	0.045	X7	0.113	0.109	0.109	0.085
x32	0.031	0.062	0.069	0.064	0.035	0.014	0.009	0.089	0.081	x18	0.095	0.082	0.078	0.068
X1	0.05	0.078	0.08	0.063	0.015	-0.031	-0.038	0.132	0.118	X11	0.093	0.081	0.070	0.081
x31	0.022	0.038	0.05	0.051	0.099	0.109	0.113	0.062	0.076	x32	0.076	0.071	0.073	0.057
x17	-0.019	0.043	0.039	0.05	0.057	0.059	0.065	0.031	0.012	X9	0.066	0.069	0.064	0.078
x18	-0.024	0.05	0.056	0.045	-0.017	-0.029	-0.036	0.056	0.058	x30	0.071	0.060	0.059	0.049
x30	0.013	0.034	0.043	0.032	-0.006	-0.02	-0.027	0.086	0.037	x33	0.071	0.052	0.055	0.028
X9	-0.074	0.024	0.024	0.027	0.039	0.039	0.033	0.054	0.004	x29	0.052	0.043	0.039	0.034
x33	-0.017	0.032	0.054	0.015	-0.056	-0.074	-0.082	0.031	-0.026	X8	0.027	0.038	0.030	0.069
x20	0.165	0.013	-0.065	0.008	0.045	0.058	0.063	-0.008	0.076	X4	0.018	0.012	0.010	0.005
x14	0.016	0.007	0.025	0.008	-0.115	-0.108	-0.109	-0.082	-0.039	x25	-0.033	-0.029	-0.024	-0.024
x23	-0.064	-0.041	-0.011	-0.024	-0.046	-0.056	-0.063	-0.057	-0.076	x26	-0.028	-0.031	-0.027	-0.033
x12	-0.065	-0.024	-0.02	-0.025	-0.002	-0.004	-0.008	-0.017	0.100	x23	-0.024	-0.040	-0.035	-0.059
x21	-0.121	-0.049	0.051	-0.029	0.038	0.072	0.076	-0.077	-0.046	x34	-0.053	-0.042	-0.049	0.022

x19	-0.063	-0.032	-0.018	-0.036	-0.059	-0.068	-0.074	-0.025	0.064	x31	-0.060	-0.047	-0.052	-0.008
X8	0.033	-0.027	-0.053	-0.039	0.012	0.032	0.043	-0.061	-0.039	x28	-0.057	-0.052	-0.047	-0.036
X5	-0.105	-0.061	-0.047	-0.041	-0.01	0.043	-0.01	0.115	0.119	x13	-0.058	-0.057	-0.061	0.044
X7	0.044	-0.026	-0.05	-0.048	-0.044	-0.026	0.003	-0.091	-0.096	x27	-0.070	-0.072	-0.065	-0.070
x34	0.042	-0.049	-0.072	-0.057	-0.022	-0.009	0.005	-0.094	-0.025	x14	-0.102	-0.088	-0.083	-0.078
x26	-0.093	-0.073	-0.048	-0.063	-0.096	-0.106	-0.112	-0.135	-0.007	x12	-0.090	-0.092	-0.044	-0.150
x15	-0.07	-0.09	-0.072	-0.073	-0.049	-0.037	-0.035	-0.093	-0.108	x35	-0.102	-0.098	-0.092	-0.073
x28	-0.127	-0.101	-0.078	-0.091	-0.099	-0.094	-0.099	-0.079	-0.015	X5	-0.106	-0.107	-0.107	-0.092
x27	-0.139	-0.106	-0.087	-0.103	-0.1	-0.1	-0.107	-0.117	-0.064	x24	-0.148	-0.108	-0.095	-0.097
x35	-0.054	-0.097	-0.119	-0.12	-0.13	-0.13	-0.132	-0.076	-0.010	x15	-0.122	-0.125	-0.124	-0.117
x22	-0.099	-0.116	-0.114	-0.126	-0.127	-0.123	-0.123	0.200	0.249	x16	-0.173	-0.153	-0.155	-0.165
x25	-0.1	-0.139	-0.139	-0.144	-0.141	-0.136	-0.124	-0.166	-0.017	x22	-0.197	-0.162	-0.142	-0.122
x29	0.001	-0.16	-0.148	-0.145	-0.142	-0.138	-0.136	0.103	0.225	x20	-0.268	-0.284	-0.275	-0.282
x24	-0.128	-0.152	-0.14	-0.149	-0.123	-0.091	-0.081	-0.027	0.156	x19	-0.306	-0.323	-0.312	-0.350

Third factor									
X3	0.227	0.262	0.297	0.379	0.322	0.259	0.335	0.341	0.302
X2	0.012	0.177	0.259	0.302	0.273	0.22	0.289	0.334	0.188
x21	0.209	0.219	0.247	0.273	0.296	0.244	0.253	0.235	0.191
x16	-0.327	0.112	0.122	0.229	0.223	0.157	0.276	0.286	0.264
X6	0.069	0.131	0.165	0.228	0.24	0.163	0.29	0.356	0.168
x20	0.048	0.124	0.18	0.22	0.199	0.184	0.261	0.183	0.082
x33	0.073	0.162	0.212	0.214	0.189	0.124	0.134	0.132	0.041
x13	0.183	0.185	0.169	0.184	0.196	0.126	0.117	-0.124	-0.146
x18	0.167	-0.014	0.123	0.153	0.179	-0.018	-0.034	0.015	0.000
X1	0.12	0.064	0.073	0.124	0.153	0.036	0.074	-0.023	-0.027
X7	-0.021	0.083	0.103	0.123	0.101	0.199	0.235	0.188	0.137
X11	0.059	0.058	0.046	0.112	0.117	0.028	0.105	0.145	0.080
X10	0.036	0.005	0.025	0.11	0.13	0.047	0.155	0.109	0.039
x30	0.123	0.071	0.077	0.099	0.131	0.033	-0.01	0.022	-0.037
X8	0.009	0.085	0.09	0.096	0.076	0.176	0.203	0.037	-0.033
x29	-0.089	-0.157	0.061	0.089	0.06	0.043	0.121	-0.061	-0.038
x35	0.037	0.049	0.051	0.067	0.011	0.013	-0.112	0.043	0.107
x32	0.072	0.013	0.02	0.052	0.09	-0.072	-0.081	-0.073	-0.037
X4	0.118	0.109	0.115	-0.005	0.18	-0.027	-0.104	-0.108	-0.021
x19	-0.094	-0.068	-0.042	-0.033	-0.009	-0.077	-0.108	-0.147	-0.133
x23	-0.032	-0.093	-0.044	-0.033	-0.001	-0.079	-0.12	-0.071	0.147
x34	0.064	0.065	0.036	-0.044	-0.067	0.07	0.044	-0.103	-0.055

Third factor				
X6	0.328	0.304	0.316	0.256
X2	0.276	0.282	0.286	0.269
X7	0.278	0.278	0.290	0.222
x21	0.240	0.270	0.284	0.238
X3	0.207	0.211	0.215	0.193
X8	0.139	0.166	0.176	0.179
x29	0.125	0.114	0.103	0.094
x17	0.036	0.083	0.093	0.078
x34	0.058	0.082	0.083	0.120
x18	0.106	0.081	-0.001	0.085
X10	0.059	0.072	0.071	0.081
x33	0.096	0.066	0.054	0.063
X1	0.063	0.060	0.059	0.046
x30	0.058	0.036	0.026	0.033
x25	-0.020	-0.015	-0.005	-0.020
x32	-0.029	-0.044	-0.045	-0.052
X9	-0.063	-0.051	-0.043	0.075
x31	-0.069	-0.054	-0.058	-0.001
x23	-0.022	-0.059	-0.077	-0.037
x28	-0.080	-0.070	-0.067	-0.051
x15	-0.061	-0.072	-0.089	-0.016
X4	-0.055	-0.072	-0.076	-0.067

x28	-0.036	-0.083	-0.059	-0.068	-0.046	-0.09	-0.142	-0.129	0.040	x14	-0.088	-0.077	-0.074	-0.071
x24	-0.072	-0.073	-0.051	-0.095	-0.099	-0.018	-0.083	-0.120	-0.095	x24	-0.123	-0.080	-0.064	-0.097
x25	-0.129	-0.129	-0.1	-0.096	-0.099	-0.056	0.048	-0.132	-0.087	x35	-0.116	-0.103	-0.108	-0.060
x17	0.034	-0.123	-0.101	-0.101	-0.066	-0.131	-0.138	-0.143	-0.092	x26	-0.109	-0.105	-0.104	-0.095
X9	-0.194	-0.144	-0.105	-0.11	-0.126	-0.09	-0.021	0.146	0.172	X11	-0.113	-0.110	-0.106	0.057
X5	-0.027	-0.058	-0.085	-0.113	-0.077	-0.115	-0.221	-0.185	-0.113	x27	-0.151	-0.149	-0.149	-0.134
x31	0.1	0.04	-0.043	-0.116	-0.076	-0.072	-0.074	0.346	0.419	x16	-0.187	-0.154	-0.171	-0.108
x15	-0.174	-0.158	-0.117	-0.135	-0.156	-0.078	-0.071	0.126	0.157	x13	-0.176	-0.175	-0.183	0.038
x26	-0.226	-0.244	-0.198	-0.136	-0.137	-0.157	-0.157	-0.346	-0.078	x12	-0.232	-0.176	-0.112	-0.180
x14	0.141	0.06	0.009	-0.165	-0.159	0.052	0.007	-0.219	-0.129	X5	-0.180	-0.185	-0.194	-0.166
x27	-0.118	-0.185	-0.189	-0.197	-0.189	-0.175	-0.183	-0.332	-0.118	x22	-0.255	-0.211	-0.196	-0.162
x22	-0.054	-0.19	-0.206	-0.249	-0.207	-0.205	-0.31	0.250	0.403	x20	-0.279	-0.312	-0.333	-0.249
x12	-0.147	-0.169	-0.205	-0.268	-0.247	-0.274	-0.342	-0.105	0.186	x19	-0.360	-0.392	-0.421	-0.342

Table 4.15 Taiwan: Ranking financial indicators by weights updated at 03M6 and 10M6

Second factor									Second factor				
ID	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	ID	09M6	10M6	11M6	12M6
x16	0.233	0.239	0.223	0.251	0.256	0.263	0.109	0.198	0.208	X10	0.246	0.235	0.244	0.205
X3	0.236	0.214	0.218	0.227	0.223	0.22	0.143	0.149	0.076	X2	0.203	0.194	0.18	0.2
x13	0.171	0.172	0.181	0.166	0.133	0.143	0.182	0.168	0.054	X3	0.176	0.166	0.149	0.172
X2	0.195	0.166	0.165	0.141	0.148	0.159	-0.018	0.034	0.038	X8	0.12	0.155	0.125	0.174
X11	0.131	0.136	0.124	0.13	0.113	0.128	-0.118	0.075	0.137	x34	0.132	0.151	0.139	0.153
X6	0.109	0.116	0.086	0.092	0.117	0.136	0.181	0.122	0.097	X6	0.125	0.127	0.122	0.118
x20	0.048	0.067	0.071	0.083	0.107	0.102	0.045	0.107	0.072	X11	0.095	0.098	0.083	0.1
X7	0.133	0.078	0.066	0.077	0.077	0.06	0.028	0.138	0.129	x22	0.106	0.089	0.076	0.086
X8	0.095	0.058	0.061	0.069	0.064	0.039	-0.034	0.071	0.087	x32	0.083	0.089	0.093	0.08
x14	0.296	0.103	0.081	0.068	0.036	0.022	0.11	0.04	0.032	X1	0.089	0.079	0.079	0.055
X10	0.045	0.064	0.054	0.064	0.076	0.092	0.132	0.07	0.075	x15	0.077	0.075	0.078	0.069
x33	0.099	0.088	0.055	0.061	0.086	0.094	0.113	0.068	0.073	X4	0.076	0.068	0.068	0.059
X1	0.044	0.048	0.03	0.04	0.059	0.084	-0.07	0.071	0.028	x24	0.062	0.051	0.046	0.039
x34	0.113	0.025	0.026	0.024	0.007	-0.031	-0.052	0.069	0.032	x20	0.058	0.034	0.041	0.013
x35	0.043	0.018	0.006	0.023	0.017	0.016	0.255	0.017	-0.028	X7	0.015	0.021	0.008	0.044
x29	0.032	0.017	0.011	0.023	0.047	0.05	-0.017	0.058	0.098	x28	0.033	0.018	0.028	-0.011
X9	-0.09	0.015	0.025	0.02	0.02	-0.012	0.057	-0.008	0.067	x21	0.013	0.015	0.018	0.014
x21	-0.152	-0.074	-0.052	0.013	0.06	0.051	0.027	0.011	-0.014	x27	-0.005	-0.005	-0.005	-0.008
x32	0.012	0.018	-0.006	-0.009	-0.007	0.033	0.105	-0.038	-0.028	x19	-0.027	-0.016	-0.03	0.03
x18	-0.032	-0.017	-0.023	-0.015	0.02	0.042	-0.182	-0.017	0.046	x16	-0.044	-0.027	-0.035	0.079
X4	-0.017	-0.012	-0.017	-0.021	-0.028	-0.014	0.064	-0.054	-0.071	x18	-0.031	-0.037	-0.035	-0.033

x30	-0.024	-0.019	-0.028	-0.022	0.014	0.037	-0.145	0.004	0.016	x35	-0.063	-0.054	-0.052	-0.047
x15	-0.05	-0.049	-0.026	-0.028	-0.026	-0.039	0.041	-0.081	-0.084	x14	-0.054	-0.058	-0.052	-0.058
x31	0.031	0.018	0.006	-0.049	-0.044	-0.048	-0.113	0.101	0.099	X9	-0.068	-0.063	-0.065	0.035
x23	-0.063	-0.061	-0.057	-0.05	-0.027	-0.003	0.013	-0.084	-0.054	X5	-0.08	-0.065	-0.056	-0.045
x19	-0.089	-0.067	-0.071	-0.06	0.005	0.024	-0.084	-0.08	-0.092	x30	-0.094	-0.098	-0.094	-0.077
x17	-0.064	-0.066	-0.056	-0.062	-0.062	-0.049	-0.135	-0.12	-0.071	x13	-0.149	-0.101	-0.09	-0.091
x25	-0.115	-0.129	-0.145	-0.116	-0.08	-0.076	0.003	-0.173	-0.05	x12	-0.107	-0.115	-0.048	-0.146
x24	-0.122	-0.125	-0.122	-0.123	-0.101	-0.113	-0.092	-0.133	-0.121	x23	-0.109	-0.115	-0.104	-0.11
X5	-0.158	-0.129	-0.125	-0.128	-0.117	-0.105	0.072	-0.058	-0.016	x33	-0.104	-0.118	-0.118	-0.113
x26	-0.222	-0.182	-0.161	-0.133	-0.099	-0.073	0.056	-0.105	-0.052	x17	-0.136	-0.125	-0.121	-0.106
x28	-0.192	-0.174	-0.172	-0.156	-0.115	-0.099	-0.024	-0.126	0.071	x31	-0.178	-0.135	-0.115	-0.099
x12	-0.175	-0.139	-0.149	-0.176	-0.184	-0.183	0.056	0.264	0.283	x29	-0.144	-0.138	-0.14	-0.153
x27	-0.241	-0.199	-0.186	-0.176	-0.142	-0.127	0.079	0.086	0.193	x26	-0.229	-0.246	-0.236	-0.245
x22	-0.172	-0.198	-0.223	-0.222	-0.194	-0.165	-0.04	0.032	0.149	x25	-0.259	-0.271	-0.256	-0.293

Table 4.16 Thailand: Ranking financial indicators by weight estimates of 01M6 and 12M6

First factor										Third factor				
ID	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6	08M6	ID	09M6	10M6	11M6	12M6
X11	0.151	0.162	0.169	0.177	0.181	0.171	0.155	0.357	0.270	x20	0.269	0.269	0.233	0.279
X2	0.165	0.161	0.166	0.116	0.097	0.072	0.044	0.198	0.194	X2	0.208	0.208	0.217	0.222
X10	0.151	0.160	0.165	0.161	0.148	0.138	0.125	0.160	0.168	X6	0.243	0.217	0.258	0.219
x16	0.132	0.142	0.167	0.198	0.206	0.204	0.196	0.062	0.105	x25	0.225	0.216	0.206	0.195
X6	0.117	0.132	0.126	0.105	0.088	0.076	0.081	0.076	0.139	x21	0.168	0.172	0.193	0.182
x26	0.092	0.101	0.107	0.095	0.066	0.034	0.004	0.080	0.110	x29	0.198	0.181	0.172	0.158
x14	0.150	0.100	0.070	0.067	0.078	0.094	0.104	0.213	0.254	x14	0.174	0.172	0.168	0.156
x13	0.082	0.093	0.091	0.088	0.091	0.098	0.082	0.049	0.044	x34	0.096	0.119	0.116	0.144
x32	0.082	0.091	0.096	0.102	0.100	0.090	0.081	0.166	0.138	X10	0.088	0.116	0.136	0.136
X3	0.071	0.075	0.082	0.074	0.055	-0.010	-0.036	-0.008	0.051	X8	0.087	0.102	0.103	0.127
X1	0.062	0.072	0.077	0.076	0.065	0.053	0.040	-0.064	0.071	x31	0.081	0.083	0.084	0.118
x17	0.066	0.067	0.078	0.082	0.087	0.093	0.101	0.189	0.111	X11	0.063	0.059	0.065	0.100
X9	0.053	0.062	0.064	0.068	0.073	0.077	0.069	0.133	-0.013	X7	0.123	0.109	0.111	0.082
x31	0.054	0.058	0.054	0.046	0.053	0.069	0.088	0.096	-0.283	x15	0.072	-0.189	-0.196	0.073
x20	0.040	0.057	0.065	0.063	0.051	0.039	0.035	0.147	-0.140	X9	-0.123	-0.105	0.053	0.072
x29	0.047	0.046	0.050	0.040	0.018	0.002	0.004	-0.132	0.037	x17	-0.077	0.043	0.070	0.071
x12	0.023	0.030	0.036	0.035	0.038	0.039	0.037	0.115	-0.013	X3	0.050	0.052	0.056	0.066
x18	0.017	0.021	0.029	0.030	0.022	0.011	-0.048	0.019	0.078	x32	0.062	0.057	0.067	0.050
x30	0.013	0.019	0.025	0.025	0.018	-0.006	-0.017	0.110	0.051	x26	0.032	0.041	0.032	0.031
X4	-0.022	-0.018	-0.021	-0.021	-0.013	-0.008	-0.018	-0.123	0.044	x18	0.064	0.029	0.007	0.024

x23	-0.042	-0.037	-0.027	-0.029	-0.036	-0.048	-0.060	-0.079	0.049	X1	0.026	0.018	0.021	0.013
x22	-0.051	-0.059	-0.061	-0.059	-0.067	-0.080	-0.089	0.077	-0.070	x35	-0.050	0.007	-0.071	-0.034
X5	-0.075	-0.067	-0.070	-0.073	-0.068	-0.062	-0.074	-0.082	-0.006	x30	0.046	-0.026	-0.038	-0.035
x34	-0.069	-0.073	-0.078	-0.078	-0.075	-0.067	-0.049	-0.094	-0.044	x28	-0.053	-0.047	-0.056	-0.043
x25	-0.069	-0.076	-0.070	-0.061	-0.069	-0.080	-0.072	-0.056	-0.077	x22	-0.117	-0.082	-0.072	-0.070
x28	-0.078	-0.078	-0.070	-0.070	-0.077	-0.085	-0.095	-0.118	-0.071	x24	-0.110	-0.065	-0.060	-0.078
X7	-0.073	-0.078	-0.085	-0.091	-0.092	-0.084	-0.073	-0.103	-0.092	x23	-0.032	-0.077	-0.095	-0.085
X8	-0.071	-0.080	-0.083	-0.088	-0.082	-0.063	-0.042	0.034	-0.041	x33	0.031	-0.080	-0.098	-0.099
x35	-0.073	-0.081	-0.089	-0.086	-0.086	-0.097	-0.116	0.506	-0.195	x16	-0.143	-0.124	-0.121	-0.126
x21	-0.113	-0.095	-0.079	-0.080	-0.080	0.010	0.029	0.067	-0.077	x13	-0.146	-0.141	-0.168	-0.136
x33	-0.125	-0.095	0.014	0.009	-0.030	-0.047	-0.068	-0.103	-0.238	x12	-0.224	-0.176	-0.082	-0.143
x15	-0.102	-0.114	-0.118	-0.125	-0.126	-0.124	-0.121	-0.125	-0.099	X4	-0.138	-0.161	-0.172	-0.162
x19	-0.123	-0.119	-0.108	-0.109	-0.115	-0.123	-0.133	0.112	0.025	x19	-0.127	-0.140	-0.170	-0.169
x27	-0.151	-0.153	-0.155	-0.157	-0.159	-0.165	-0.175	-0.158	-0.116	X5	-0.184	-0.188	-0.224	-0.194
x24	-0.147	-0.158	-0.160	-0.164	-0.169	-0.165	-0.149	-0.261	-0.419	x27	-0.367	-0.351	-0.348	-0.336

Table 4.17 Sum Squares of Shifted weight estimators across indicators

Ajacent rounds	1–2	2–3	3–4	4–5	5–6	6–7	7–8	8–9	9–10	10–11	11–12	12–13
SG: $3rd \to 1st$	0.421	0.467	0.270	0.081	0.549	0.866	0.216	0.103	0.294	0.014	0.053	0.033
KOR: $1st \to 2nd$	0.454	0.126	0.100	0.123	0.297	0.146	0.044	0.463	1.635	0.023	0.018	0.175
TW: $2nd \to 2nd$	0.077	0.007	0.013	0.022	0.012	0.029	0.007	0.130	0.714	0.009	0.008	0.049
TH: $1st \to 3rd$	0.006	0.015	0.005	0.005	0.018	0.011	0.007	0.992	0.848	0.117	0.050	0.090
AVE	0.240	0.154	0.097	0.058	0.219	0.390	0.055	0.422	0.872	0.041	0.032	0.087

Table 4.18 Sum Squares of Shifted weight estimators across out-of-sample intervals

ID	SG		TH		KOR				TW		AVE	
	pre-3rd	post-1st	pre-1st	Post-3rd	pre-1st	pre-3rd	post-2nd	post-3rd	pre-2nd	post-2nd	Pre	post
X1	0.02	0.005	0.001	0.027	0.001	0.022	0.001	0.006	0.002	0.001	0.009	0.008
X2	0.161	0.044	0.004	0	0.028	0.044	0.005	0.029	0.002	0.022	0.048	0.02
X3	0.057	0.038	0.005	0.021	0.005	0.022	0.002	0.037	0.002	0.029	0.018	0.026
X4	0.014	0.002	0	0.002	0	0.098	0.01	0.003	0	0.009	0.023	0.005
X5	0.037	0.008	0	0.005	0.001	0.016	0	0.012	0.001	0.01	0.011	0.007
X6	0.058	0.002	0.001	0.011	0.003	0.031	0.001	0.007	0.004	0.003	0.019	0.005
X7	0.02	0.004	0	0.023	0.001	0.023	0.001	0.014	0.004	0.004	0.01	0.009
X8	0.031	0.004	0.001	0.013	0.001	0.017	0	0.014	0.002	0.005	0.01	0.007
X9	0.039	0.007	0	0.181	0.034	0.01	0.034	0.047	0.013	0.002	0.019	0.054
X10	0.009	0.055	0.001	0.008	0.003	0.028	0.004	0.009	0.001	0.002	0.008	0.016
X11	0.022	0.006	0.001	0.023	0.001	0.018	0.001	0.108	0.001	0.001	0.009	0.028
X12	0.052	0.02	0	0.047	0.005	0.012	0.003	0.107	0.002	0.033	0.014	0.042
X13	0.071	0.002	0	0.068	0.01	0.006	0.005	0.16	0.002	0.038	0.018	0.055
X14	0.201	0.002	0.004	0.003	0.04	0.086	0.009	0.046	0.04	0.006	0.074	0.013
X15	0.204	0.007	0	0.284	0.122	0.009	0.096	0.096	0.001	0.01	0.067	0.098
X16	0.257	0.035	0.002	0.915	0.904	0.222	1.705	0.379	0.001	0.183	0.277	0.643
X17	0.025	0.011	0	0.046	0.003	0.031	0.003	0.036	0.001	0.011	0.012	0.022
X18	0.064	0.001	0.004	0.065	0.008	0.093	0.013	0.033	0.002	0	0.034	0.022
X19	0.018	0.05	0	0.066	0.007	0.008	0.007	0.392	0.005	0.181	0.008	0.139
X20	0.018	0.093	0.001	0.019	0.009	0.017	0.009	0.498	0.001	0.19	0.009	0.162
X21	0.576	0.011	0.009	0.013	0.332	0.005	0.111	0.004	0.013	0.005	0.187	0.029
X22	0.039	0.038	0	0.006	0.003	0.033	0.003	0.068	0.003	0.103	0.016	0.044
X23	0.085	0.007	0	0.008	0.007	0.015	0	0.011	0.003	0.008	0.022	0.007
X24	0.28	0.018	0	0.005	0.079	0.013	0.007	0.005	0.001	0.011	0.075	0.009
X25	0.027	0.005	0	0.029	0.002	0.014	0.001	0.005	0.01	0.001	0.011	0.008
X26	0.006	0.002	0.003	0.01	0	0.007	0	0.003	0.005	0.001	0.004	0.003
X27	0.024	0.001	0	0.037	0.002	0.005	0.001	0.007	0.003	0	0.007	0.009
X28	0.065	0.002	0	0.005	0.004	0.008	0	0.003	0.003	0.002	0.016	0.002
X29	0.016	0.003	0.001	0.015	0.001	0.06	0.004	0.016	0.001	0.003	0.016	0.008
X30	0.033	0.001	0.001	0.028	0.002	0.016	0.001	0.013	0.002	0	0.011	0.009
X31	0.021	0.001	0.001	0.04	0.002	0.017	0.002	0.006	0.004	0.025	0.009	0.015
X32	0.014	0.001	0	0.006	0	0.032	0.001	0.001	0.003	0.001	0.01	0.002
X33	0.045	0.001	0.015	0.018	0.003	0.015	0.001	0.006	0.002	0.003	0.016	0.006
X34	0.033	0.008	0	0.004	0.001	0.027	0.001	0.006	0.01	0.004	0.014	0.004
X35	0.007	0	0.001	0.049	0.002	0.019	0.003	0.005	0.008	0	0.008	0.011

Table 4.19 Summary of leading degree and significant indicators

	More significant leading Market Misalignment types	
	Pre-2008 crisis	Post-2008 crisis
SG	MRate, Deriv	MRate, Deriv
KOR	Deriv, RRate, HPEP	Deriv, RRate, HPEP
TW	Deriv, RRate, HPEP	CIP, GOV, Deriv
TH	MRate, Deriv, RRate	CIP, ECPI, Deriv, RRate, HPEP
	Market Misalignment types with significant weight estimators	
	Pre-2008 crisis	Post-2008 crisis
SG	BE, ECPI, MRate, Deriv, RRate	Mrate, TED, MB, Deriv, RRate, HPEP
KOR	BE, CIP, ECPI, GOV, MRate, MB, Deriv, RRate	BE, CIP, ECPI, GOV, MRate, TED, MB, Deriv, RRate
TW	BE, ECPI, GOV, MRate, TED, MB, Deriv	BE, CIP, ECPI, GOV, MB, Deriv, RRate, HPEP
TH	BE, ECPI, GOV, MRate, Deriv, HPEP	CIP, ECPI, GOV, MRate, TED, Deriv, HPEP

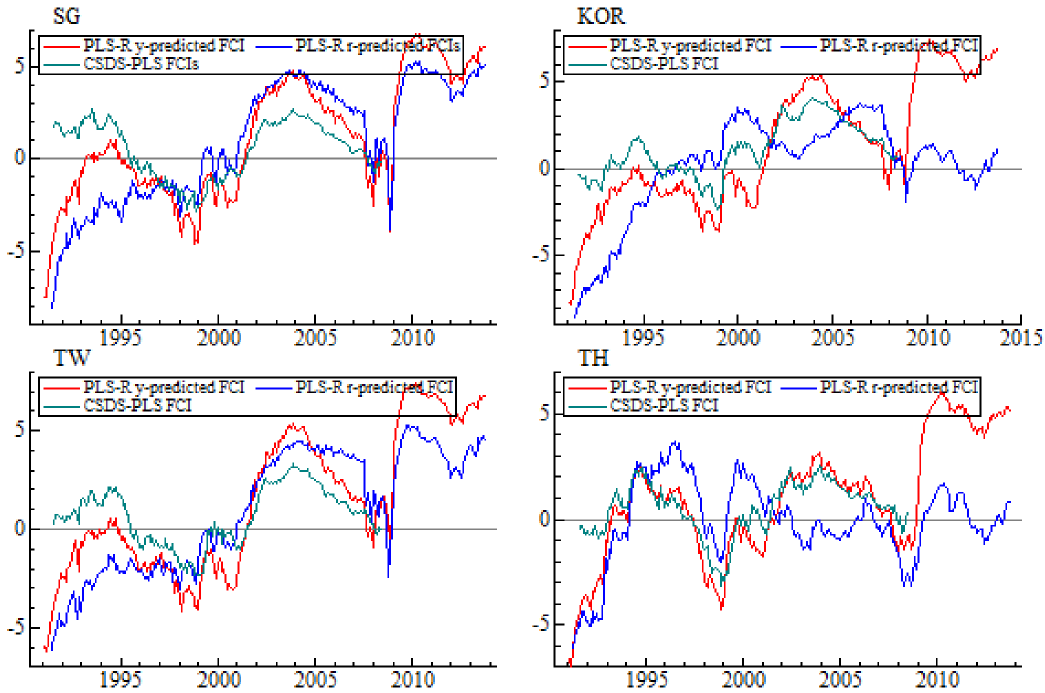

Figure 4.1 In-sample CSDS–PLS FCIs, PLS-R y-predicted FCIs and PLS-R r-predicted FCIs

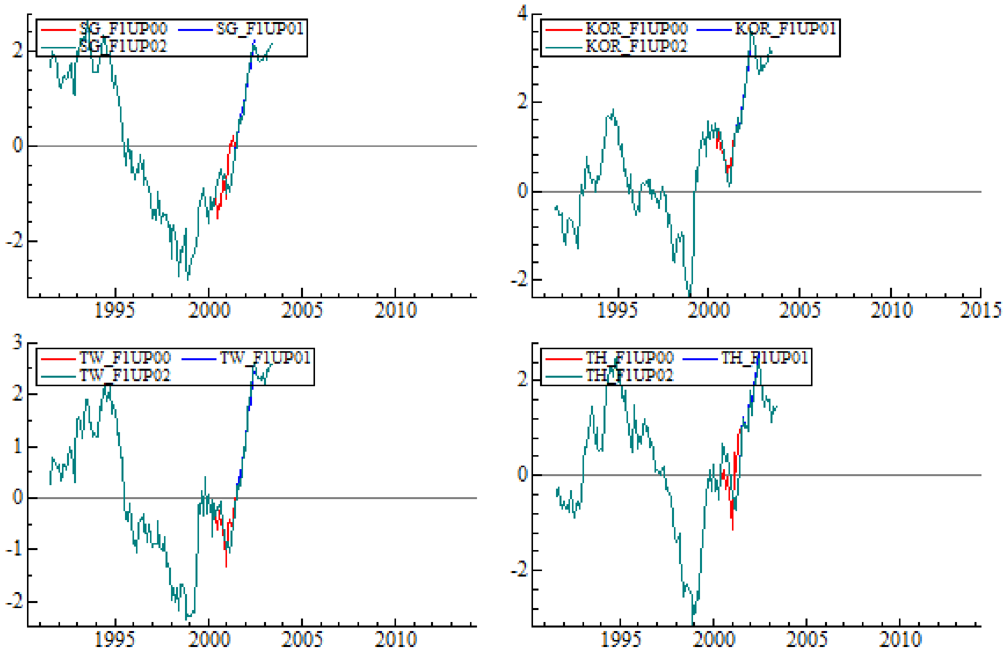

Figure 4.2 CSDS–PLS FCIs updated at 00M7–01M6, 01M7–02M6, and 02M7–03M6 out-of-sample intervals

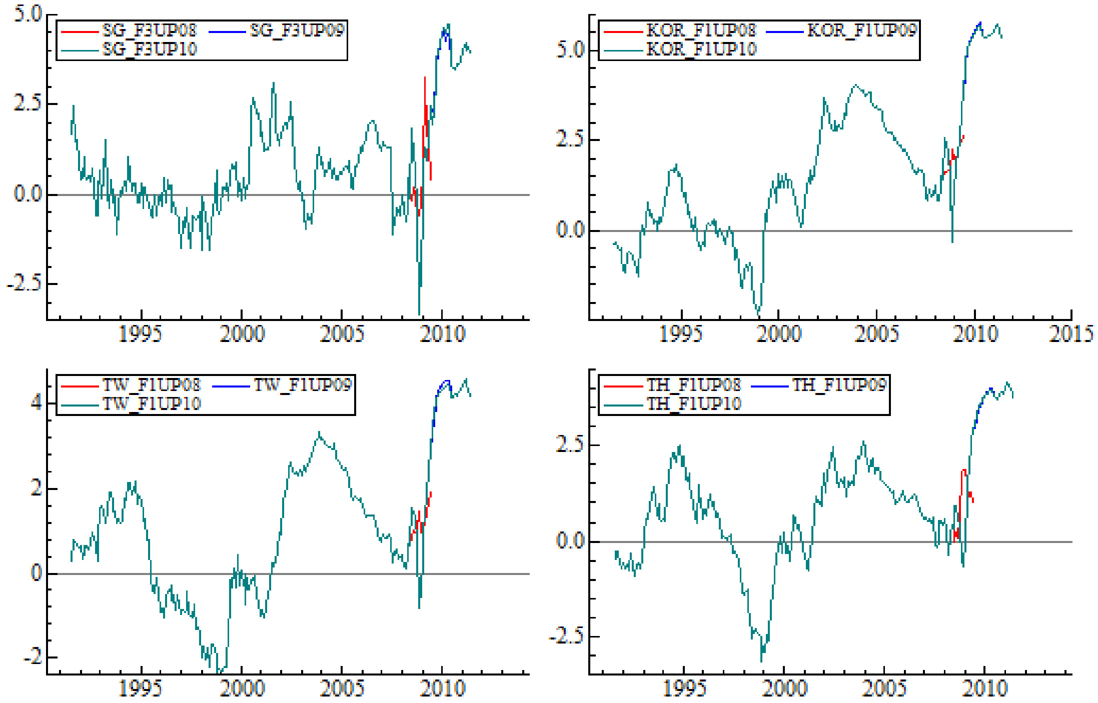

Figure 4.3 CSDS–PLS FCIs updated at 08M7–09M6, 09M7–10M6, and 10M7–11M6 out-of-sample intervals

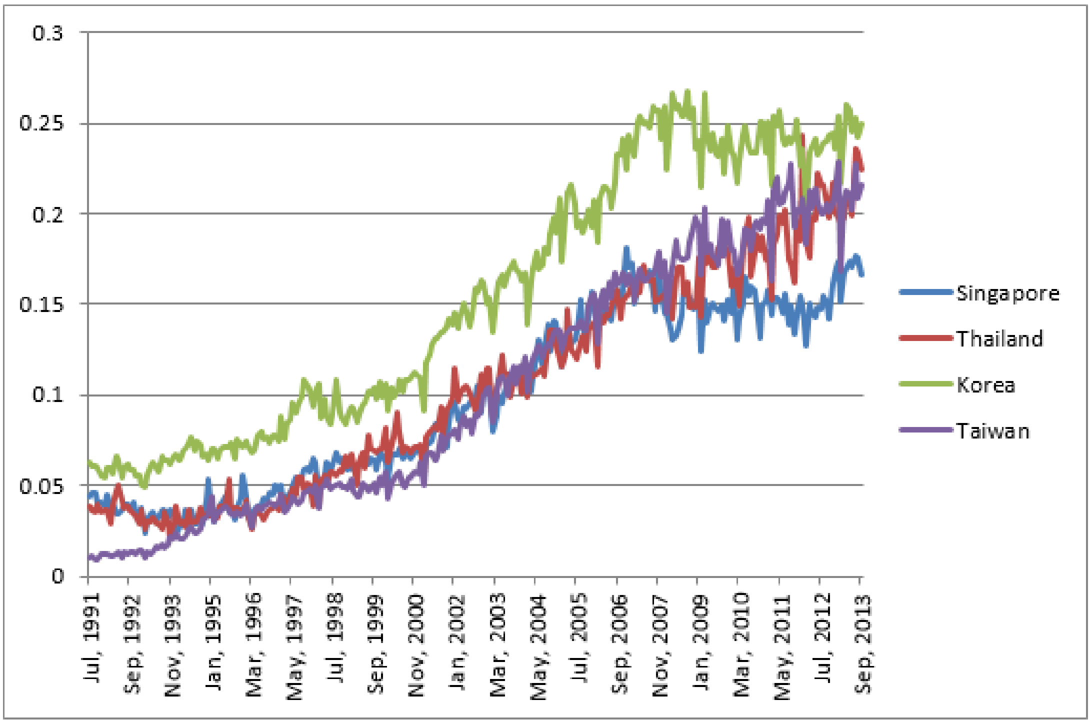

Figure 4.4 Ratio of import volume from China to total import volume

Chapter 5 A Concatenated RDS–PLS approach

5.1 Introduction

Based on the superior predictive power of CSDS–PLS FCIs found in Chapter 4, this chapter further investigates disaggregate dynamics by constructing a Revised Dynamic Sparse PLS FCIs that are also concatenated (henceforth, CRDS–PLS FCIs).[100] It is then this chapter's main task to test whether CRDS–PLS FCIs can improve the forecasting performance of the import price index more than CSDS–PLS FCIs. Since among the PLS-R y-predicted, r-predicted FCIs, and CSDS–PLS FCIs, CSDS–PLS FCIs have better forecasting performance than both PLS-R y-predicted FCIs and PLS-R r-predicted FCIs, this chapter puts its focus on the predictive tests of CRDS–PLS FCIs vs. CSDS–PLS FCIs' forecasting models and of CRDS–PLS FCIs vs. the benchmark forecasting model.

This chapter is organized as follows. A Revise Dynamic Sparse PLS (henceforth, RDS–PLS) method is introduced in Section 5.2. Specifically, compared to SDS–PLS method, RDS–PLS can model disaggregate dynamics more flexibly, and, further, avoid an inherited dynamic misspecification issue when a first few SDS–PLS factors are used as proxy for FCIs. Section 5.3 discusses the experimental design adopted in this chapter; Section 5.4 carries out predictive tests of CRDS–PLS FCIs vs. CSDS–PLS FCIs, and of CRDS–PLS FCIs vs. the benchmark model. At the disaggregate level, Section 5.5 investigates the dynamic forms of financial indicators. A final conclusion can be found in Section 5.6.

5.2 PLS-R y-predicted FCIs and SDS–PLS FCIs vs. RDS–PLS FCIs

This section first explains how the RDS–PLS method is used to improve the modelling of the disaggregated dynamics by comparing it with the PLS-R method used in Chapter 3 and the SDS–PLS method used in Chapter 4. Then, it explains why the use of multiple SDS–PLS factors threatens inherited disaggregate dynamic misspecifcation, while the use of multiple RDS–PLS factors does not.

[100] The superiority of concatenation is proved in the last chapter.

5.2.1 Rethinking of PLS FCIs in the framework of PLS path modelling

As Exhibit 5.1 shows, in general, RDS–PLS belongs to the methodology of PLS path modelling (henceforth, PLS–PM), or, more specifically, a mix of both reflective mode and formative mode, while PLS-R is equivalent to the reflective mode of PLS–PM.

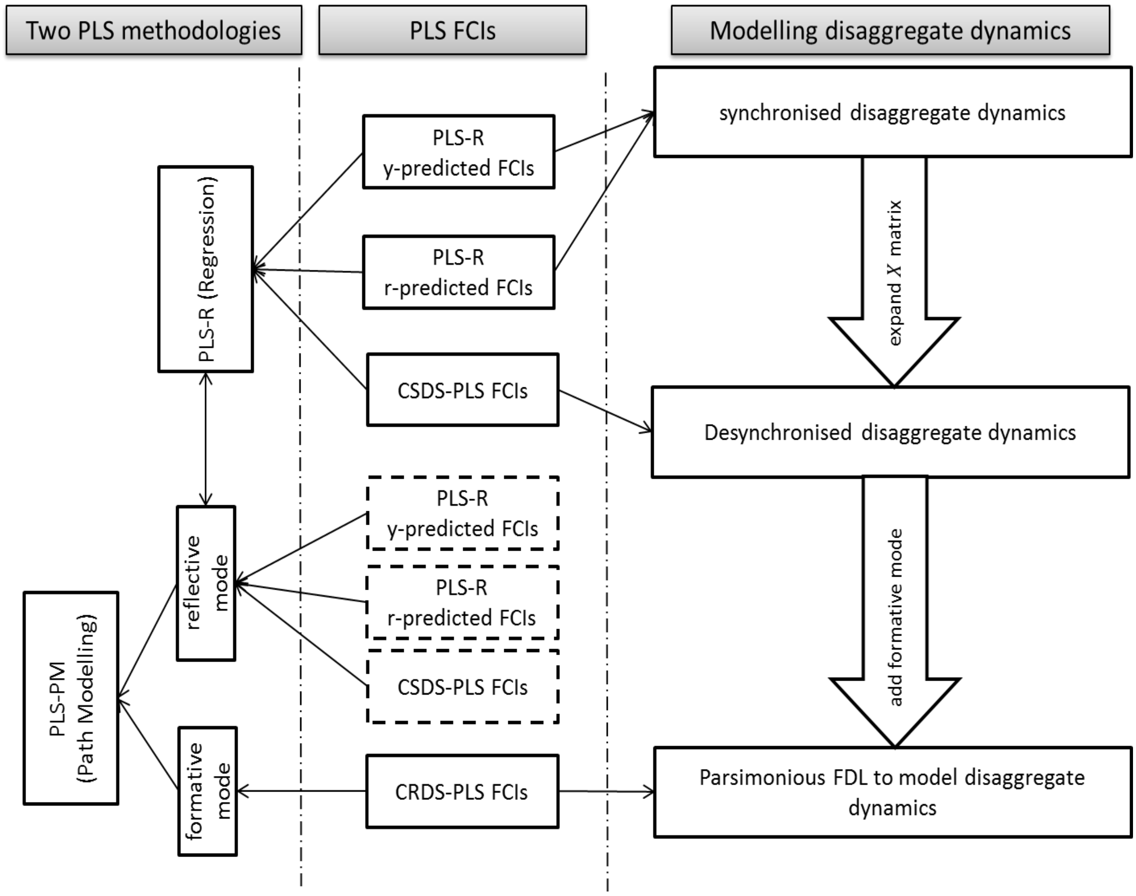

Exhibit 5.1 Linking PLS methodologies with modelling disaggregate dynamics through PLS FCIs[101]

Before an explanation for Exhibit 5.1, an elaboration of PLS–PM methodology, and its reflective mode and formative mode is necessary. PLS–PM was proposed by Wold (1980) and presented as a graphical illustration. The elaboration starts by introducing Wold's graphical illustration of Path Modelling, as it enables us to more intuitively (rather than by a mathematical explanation) understand the reflective mode that PLS-R y-predicted and SDS–PLS FCIs follow and the mixed mode that RDS–PLS FCIs follow. Essentially, Wold (1980) used a path model to describe a theoretical latent variable structure among multiple blocks of manifest variables

[101] The arrowed line denotes the parent–children relation and the dashed box denotes the same FCIs copied. For example, PLS-R y-predicted FCIs belong to PLS-R methodology, and since PLS-R is equivalent

(observable). The manifest variables are grouped into different blocks according to their general attribute, say sociological or political variables. Then, variables of each block are used to construct latent variables (unobservable), and they are linked to each other by a one-way path.

Following this idea, a two-block latent structure is adopted from Exhibit 5.2 to Exhibit 5.4, where all financial indicators form a block, and the single target variable forms another block. The latent FCIs are then constructed from the financial indicator block. Wold (1980) prepared some diagrammatical notations in order to differentiate the three modes.

- Rectangle for the observable financial indicators;
- Circle for the unobservable FCIs to be constructed from financial indicators;
- Solid curved arrow for the 'path' between FCIs and the target;
- Dashed curved arrow for the key link between financial indicators and FCIs, that is, the mode.

After the preparation of these notations, the three modes can be described.

- The dashed curved arrow directed from FCIs towards the financial indicators describes the reflective mode, in which a bivariate OLS regression of the target on an individual financial indicator is used for a weight estimate;
- The dashed arrow directed inwards from multiple financial indicators (or an individual financial indicator of multiple lags) to FCIs describes the formative mode, in which a multiple OLS regression of the target on multiple financial indicators (or an individual financial indicator with multiple lags) is used for a weight estimate.
- The mixed mode approach in this context is a simple mix of reflective mode and formative modes.

From Exhibit 5.2 to Exhibit 5.4, the modes that the three types of FCIs—the PLS-R y-predicted, SDS–PLS FCIs, and RDS–PLS FCIs—follow can be explained. In addition, these exhibits also show how the restriction on modelling the disaggregate dynamics is gradually relaxed. Exhibit 5.2 demonstrates the reflective mode that the PLS-R y-predicted FCIs follow, where the N-dimensional financial indicators are reduced into three factors by an iterative least squares algorithm. The exhibit shows that, in terms of weight estimation, the reflective mode is equivalent to a bivariate OLS regression where each financial indicator is a regressor; In terms of modelling the disaggregate dynamics, the PLS-R method has an extreme restriction that lagged financial indicators of the same length are used to model the

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to the reflective mode of PLS–PM (double-arrowed line), PLS-R y-predicted FCIs also follow the reflective mode of PLS–PM.

target in each equation. To put it another way, all financial indicators are assumed to have a synchronized leading effect on the target

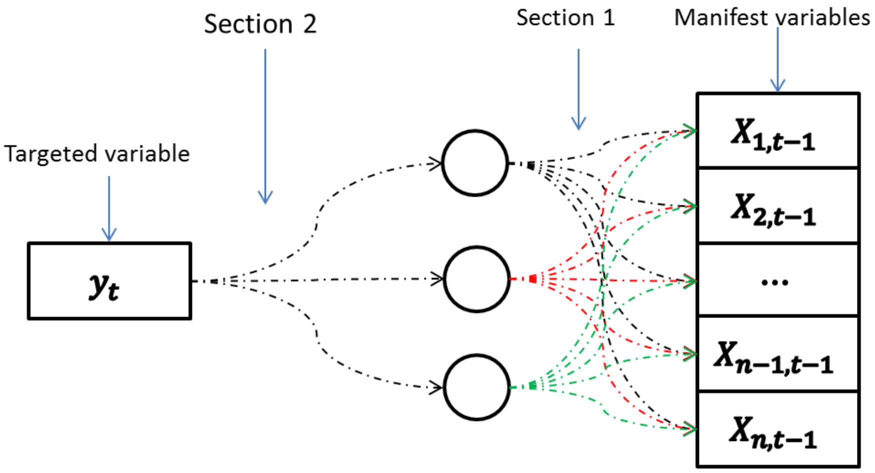

Exhibit 5.2 Diagrammatical illustrations for PLS-R y-predicted FCIs

Exhibit 5.3 demonstrates the reflective mode that the SDS–PLS FCIs follow. It shows that the weight estimates are obtained through a bivariate OLS regression, where each lag of an individual financial indicator is a regressor. In the context of the SDS–PLS method, only one weight estimate is retained with respect to each financial indicator[102] in order to filter out any redundant disaggregate dynamics (see Chapter 4). In terms of the disaggregate dynamics, SDS–PLS FCIs relax the extreme restriction in the sense that financial indicators can have a desynchronized leading effect. It is noteworthy, however, that SDS–PLS FCIs have an over-restrictive assumption—only one lag in the level form is allowed to model the target with respect to an individual financial indicator. For example, it is the i_2-month lagged X_2, the $X_{2,t-i_2}$, that models the target, while dynamic forms, such as lagged X_2 in the differenced form $\Delta X_{2,t-i_2}$, are not allowed to model the target.

[102] In total there are 6 weight estimates corresponding to 6 lags of an individual financial indicator. In fact, SDS–PLS FCIs moves one step further from a typical PLS path modelling method. That is, PLS path modelling does not require any assumption on residual distribution, while the construction of SDS–PLS FCIs relies on residual normality to filter out desynchronized leading information.

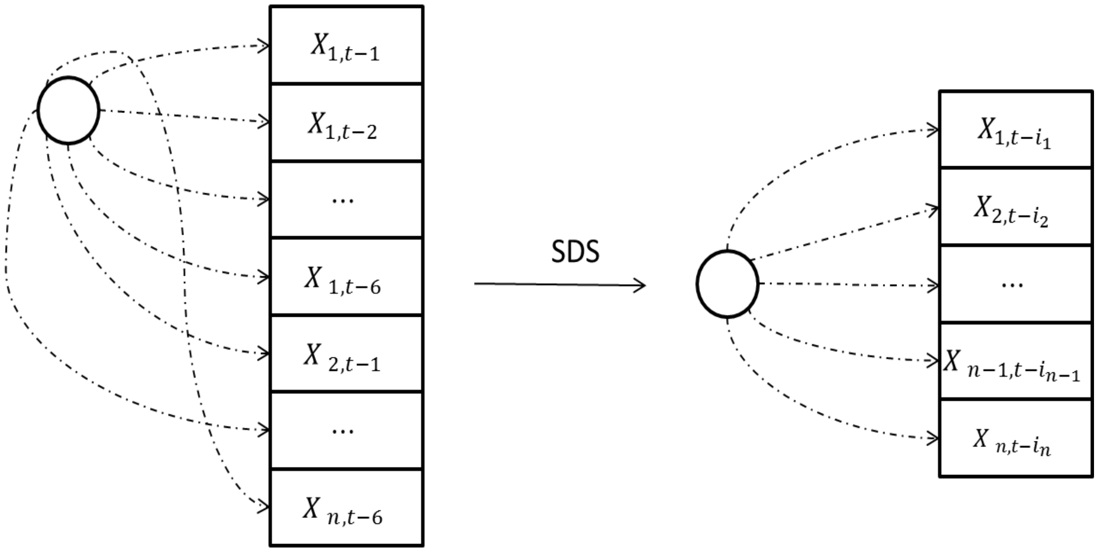

Exhibit 5.3 Diagrammatical illustrations for PLS-R y-predicted FCIs

By contrast, Exhibit 5.4 demonstrates a mixed mode that RDS–PLS FCIs follow. On the left side of Exhibit 5.4, lagged indicators, that is, up to 6-month lagged, are grouped into a sub-block, and they function as regressors in a multiple regression model. The multiple regression model is actually a Finite Distributed Lags (henceforth, FDL) model, that is, a restricted Autoregressive Distributed Lag model class classified by Hendry (1995). As noted by Clements and Hendry (1998,), when focusing on the selection for a lag (a regressor in the multiple regression model), a single t-test can be applied in the parsimony process. The right side of Exhibit 5.4 then exemplifies the parsimonious dynamic specification following the parsimony procedure proposed by Clements and Hendry (1998). The differenced X_1, the differenced and 6-month lagged X_3 follow the formative mode, while the 2-month lagged X_2 follows the reflective mode. In summary, RDS–FCIs can further relax the over-restrictive assumption of SDS–FCIs in the sense that financial indicators can have various dynamics forms of the lag, rather than a single lag in the level form.

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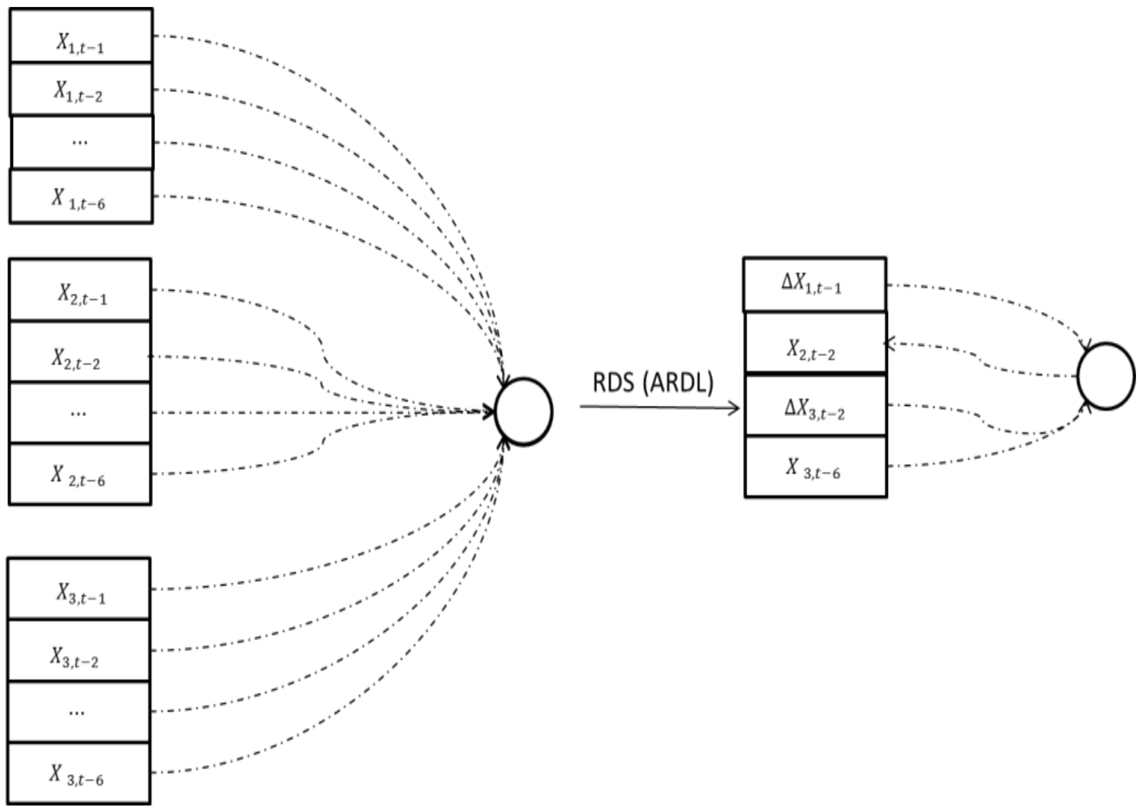

Exhibit 5.4 Diagram illustrations for CRDS–PLS FCIs

Let me come back to explain Exhibit 5.1. Both PLS-R y-predicted and r-predicted FCIs are assumed to model synchronized disaggregate dynamics. By expanding the indicator matrix with their own lags, CSDS–PLS FCIs can model desynchronized disaggregate dynamics. However, the three types of FCIs follow the reflective mode that is over-restrictive for modelling the disaggregate dynamics; CRDS–PLS FCIs that follow the mixed mode is used in this chapter.

5.2.2 Inherited misspecification of disaggregate dynamics

Moreover, compared to CRDS–PLS FCIs, the use of the first three CSDS–-PLS factors has a fatal weakness. If the disaggregated dynamics of an individual indicator is misspecified in constructing the first factor, the disaggregated dynamics of the same indicator is also misspecified in the second and third factor.

This weakness can be illustrated by the iterative least squares algorithm (see Appendix 3A). Since the algorithm is repetitive in estimating the first three PLS factors, only the estimation procedure of the first two factors is discussed here. The weight matrix of the first SDS–PLS factor is estimated as:

$$W_1 = \arg\max\{W_1{}^T X_{exp}^T Y Y^T X_{exp} W_1\}, with\ \|W_1\| = 1 \tag{5.1}$$

Here, W_1 denotes the weight vector of first factor; X_{exp} refers to the expanded financial indicator matrix (after standardization); and Y refers to the target variable.

It is notable that the X matrix is dynamically expanded as in Chapter 4:

$$X_{exp} = \left(x_{1,t-1} \quad x_{1,t-2} \quad x_{1,t-3} \quad x_{1,t-4} \quad x_{1,t-5} \quad x_{1,t-6} \quad ,\dots, \quad x_{N,t-1} \quad ,\cdots, \quad x_{N,t-6}\right) \tag{5.2}$$

The weight vector of the second SDS–PLS factor, the W_2, is similar to Equation (5.1)

$$W_2 = \arg\max\{W_2{}^T \hat{X}_{exp}^T \hat{Y}\hat{Y}^T \hat{X}_{exp} W_2\}, \text{ with } \|W_2\| = 1 ,$$

(5.3)

except that the indicator matrix is reduced into an OLS residual matrix $\hat{X}_{exp}$, which is estimated as follows:

$$X_{exp_i} = X_{exp}\,\hat{W}_1 B_i + \varepsilon_i$$

$$\hat{B}_i = \left(\hat{W}_1{}^T X_{exp}^T X_{exp} \hat{W}_1\right)^{-1} \hat{W}_1{}^T X_{exp}^T X_{exp_i}$$

$$\hat{B} = (\hat{W}_1{}^T X_{exp}^T X_{exp} \hat{W}_1)^{-1} \hat{W}_1{}^T X_{exp}^T X_{exp} \tag{5.4}$$

where $1 \le i \le N \times 6$.

Therefore,

$$\hat{X}_{resid_i}^{SDS-PLS} = \hat{\varepsilon}_i$$

$$= X_{exp} - X_{exp}(\hat{W}_1{}^T X_{exp}^T X_{exp} \hat{W}_1)^{-1} \hat{W}_1{}^T X_{exp}^T X_{exp} \tag{5.5}$$

Here, X_{exp_i} denotes the ith column vector of the expanded indicator matrix X_{exp}. Equation (5.4) states that X_{exp_i} is regressed on the first SDS–PLS factor, $X_{exp} \cdot \hat{W}_1$. And it results in an OLS coefficient $\hat{B}_i$, namely factor loadings of X_{exp}, and a residual vector $\hat{\varepsilon}_i$. Then, each $\hat{\varepsilon}_i$ is placed into the ith column of residual matrix $\hat{X}_{resid}^{SDS-PLS}$ in Equation (5.5).

The inherited biased estimator of weight is due to the dynamic misspecification of CSDS–PLS FCIs. The estimation process of W_{1_i}, namely the ith value of the weight vector of first CSDS–PLS factor, in Equation (5.1), is equivalent to the OLS estimate of Y regressed on each column vector, the X_{exp_i}. (See Section 5.2).

$$Y = W_{1_i} X_{exp_i} + u_i \tag{5.6}$$

If Equation (5.6) is misspecified and W_{1_i} is by chance retained, $\hat{W}_{2_i}$ will be a biased estimator, as explained by Exhibit 5.5:

$$\widehat{W}_{1_i} \xRightarrow{Equation\,(5.4)} \hat{B}_i \xRightarrow{Equation\,(5.5)} \hat{X}^{SDS-PLS}_{resid_i} \xRightarrow{Equation\,(5.3)} \widehat{W}_{2_i}$$

Exhibit 5.5 The causality chain to derive the inherited biased weight estimator

Exhibit 5.5 indicates that, if $\hat{W}_{1_i}$ is a biased estimator, the first factor is constructed with bias. Then, the factor-loading estimator, $\hat{B}_i$ in Equation (5.4), is also biased. Afterwards, the residual matrix of X_{exp}, $\hat{X}^{SDS-PLS}_{resid_i}$ in Equation (5.5) is misspecified. Finally $\hat{W}_{2_i}$ is a biased estimator of the weight for the second factor.

By contrast, CRDS–PLS FCIs can correct for the dynamic misspecification from the first factor onwards by a parsimony process of the following multiple regression model,

$$Y = W_{1_{vec(n)}} X_{exp_{vec(n)}} + u_n^{RDS-PLS} \tag{5.6'}$$

Note: $1 \leq n \leq N$; the difference in model specification between (5.6') and (5.6) is graphically illustrated in Exhibit 5.6.

$$X_{exp} = (\overbrace{x_{1,t-1}\quad x_{1,t-2}\quad x_{1,t-3}\quad \underset{\substack{\uparrow \\ X_{exp_4}}}{x_{1,t-4}}\quad x_{1,t-5}\quad x_{1,t-6}}^{X_{exp_{vec(1)}}}\ , \dots ,\ \overbrace{x_{n,t-1}\ , \cdots ,\ \underset{\substack{\uparrow \\ X_{exp_{6n}}}}{x_{n,t-6}}}^{X_{exp_{vec(n)}}})$$

Exhibit 5.6 Model specification difference between Equation (6) and Equation (6')

And the modelling of disaggregate dynamics by CSDS–PLS is equivalent to a parsimony process of the FDL model.

5.3 Experimental design

In a number of settings, the empirical design of this chapter is similar to those of Chapter 4.

- Because of lack of observations, only Singapore, Korea, Taiwan, and Thailand are reserved for research;
- FCIs with weights estimated both by CSDS–PLS and CRDS–PLS are updated through concatenation on an annual basis for practical reasons, and it is worth noting that the first CSDS–PLS factors estimated in the last chapter have been directly used in this chapter;
- Three types of forecasting models—the CSDS–PLS, CRDS–PLS and the benchmark forecasting models—are re-estimated with respect to the successive out-of-sample intervals; (see the concatenation method in Chapter 4);
- A one-year, ongoing, out-of-sample encompassing test is carried out corresponding to each update: (5) with regards to the out-of-sample forecasted macro predictors (in all three types of forecasting models), real value is used for the world export price index and FCIs, and the predicted value by the Auto-Regressive model are used for other macro predictors; (6) the in-sample surviving forms of FCIs, both by SDS–PLS and RDS–PLS in each update are summarized for all four target economies; and (7) the same four statistics evaluating the forecasting performance are reported as was done in Chapter 4, that is, SRRMSE, P-SRRMSE, CRRMSE, and P-CRRMSE, and the comparison of RDS–PLS vs. the benchmark and SDS–PLS forecasting models are mainly evaluated by SRRMSE and P-SRRMSE.

Except for these similar settings, a setting is different from that in Chapter 4 as discussed in the following Subsections. That is, the selection of the first factor only with respect to the CSDS–PLS and CRDS–PLS factors, compares to all the first three factors being selected in Chapter 4.

As to the determination of the number of factors to be used to represent FCIs, it is necessary to first review the number of factors used in Chapter 4. Chapter 4 used three CSDS–PLS factors because (1) by construction, the first few CSDS–PLS FCIs should have more predictive information than the first few PLS-R y-predicted FCIs due to the method's ability in modelling synchronized[103] leading information at the disaggregate level; and (2) the use of three factors

[103] As pointed out in Chapter 4, because SDS–PLS FCIs are concatenated, they are not directly comparable to PLS-R y-predicted FCIs, which are not concatenated.

more accurately describes disaggregate dynamics than the use of the first CSDS–PLS factor only.

Admitted that CRDS–PLS FCIs are less likely to have misspecified disaggregate dynamic forms, the first CSDS–PLS and CRDS–PLS factor is compared in terms of the predictive power in this chapter. The trade-off between predictive power (judging by out-of-sample RMSE) and economic interpretation at the disaggregate level favours the use of the first factor only. Although the first three CRDS–PLS factors vs. first three CSDS–PLS factors can probably result in a higher margin (in terms of predictive power) in favour of CRDS–PLS FCIs than a single CRDS–PLS factor vs. a single CSDS–PLS factor, the disaggregate analysis of first three CRDS–PLS factors is much more complex than that of first three CSDS–PLS factors.

As a practical example, if the parsimonious FDL model regarding X_i is $Y = 0.3X_{i,t-2} - 0.15X_{i,t-3}$, reducing $0.3X_{i,t-2} - 0.15X_{i,t-3}$ from $X_{i,t-1}$, the residual X_i^{resid} is obtained as $X_{i,t-1} - 0.3X_{i,t-2} + 0.15X_{i,t-3}$. Then by regressing Y_t on up to 6 lags of X_i^{resid}, the disaggregated component (X_i), the second RDS–PLS factor is constructed. If the parsimonious FDL model regarding X_i^{resid} is $Y = 0.2X_{i,t-2}^{resid} + 0.1X_{i,t-3}^{resid}$, the final dynamics form of X_i in constructing second RDS–PLS factor would be $0.2(X_{i,t-1} - 0.3X_{i,t-2} + 0.15X_{i,t-3})_{t-2} + 0.1(X_{i,t-1} - 0.3X_{i,t-2} + 0.15X_{i,t-3})_{t-3}$, which is quite complex.

5.4 Empirical Results I

Because Chapter 4 shows that the forecasting performance of CSDS–PLS FCIs pre-2008 crisis is very different from that post-2008 crisis, this section shall investigate, respectively, the forecasting performance of CRDS–PLS FCIs pre-2008 crisis and post-2008 crisis. In general, this section finds that the CRDS–-PLS FCIs outperform the CSDS–PLS FCIs and the benchmark model as to most of the out-of-sample intervals pre-2008 crisis and several intervals post-2008 crisis. Furthermore, an interval-matching pattern is found. As to those out-of-sample intervals where CSDS–PLS FCIs outperform the benchmark model, CRDS–PLS FCIs outperform the CSDS–PLS FCIs' forecasting model; as to those out-of-sample intervals when CSDS–PLS FCIs underperform the benchmark model, CSDS–PLS FCIs also underperform the benchmark model.

Subsection 5.4.1 discusses the in-sample model specification of FCIs' forecasting models, especially with respect to the dynamic specification of CRDS–PLS and CSDS–PLS FCIs in-sample.

Subsection 5.4.2 shows the superior predictive power of the CRDS–PLS FCIs, respectively, for the pre-2008 crisis and post-2008 crisis.

5.4.1 In-sample model estimation

By using Table 5.2, this subsection primarily investigates the in-sample dynamic forms of CSDS–PLS and CRDS–PLS FCIs, that is, either in the level form or in the differenced form, across the four target economies.

From Table 5.2, the level RDS–PLS FCIs generally are survived across all four economies except in the case of Thailand, while the differenced SDS–PLS FCIs are survived across all four economies. The further subsample predictive tests find that despite being mixed with the differenced form, the level CRDS–PLS FCIs are always in-sample significant with respect to Singapore, Korea, and Taiwan pre-2008 crisis. Two postulations can be made based on these findings.

First postulation: Since the level CSDS–PLS FCIs are in-sample insignificant with respect to all four economies, and either pre-2008 crisis or post-2008 crisis, it can be postulated that the improvement in predictive power is more significant in longer horizons (4–6 months ahead) because of the low frequency nature of level FCIs.[109]

Second postulation: However, as repeatedly argued in last two chapters (Chapters 3 and 4), the level (CRDS–PLS) FCIs may have much worse forecasting performance than differenced (CSDS–PLS) FCIs because of potential location shift issue. From Figure 5.1 to Figure 5.4, CRDS–PLS FCIs exhibit a large location shift during the 2008 crisis. It therefore can be postulated that a more significant forecasting failure is expected for the level RDS–PLS FCIs forecasting model than for the differenced SDS–PLS FCIs forecasting model during 2008 crisis, simply because the location shift is largely differenced out in differenced SDS–PLS FCIs.

The two postulations—the superior forecasting performance of the level RDS–PLS FCIs over the differenced SDS–PLS FCIs in longer horizons and the underperformance of level RDS–PLS FCIs when compared to SDS–PLS FCIs post-2008 crisis—will be verified in the following Subsection 5.4.2.

[109] Note that both in the last chapter and in this chapter, FCIs are *ex post* values such that the improvement of forecasting accuracy is not as significant as those that are *ex ante* forecasted.

5.4.2 Out-of-sample encompassing test results

This subsection is organized as follows. By using Tables 5.4–5.7, the superiority of RDS–PLS FCIs against the benchmark and SDS–PLS FCIs model pre-2008 crisis are found, respectively. In this process, the first postulation is verified. Finally the second postulation is verified.

The CRDS-PLS vs. Benchmark forecasting model pre-2008 crisis

The superiority of RDS–PLS FCIs is first verified by the predictive test of CRDS–PLS FCIs vs. the benchmark forecasting model with respect to the out-of-sample intervals pre-2008 crisis. From Table 5.4 to Table 5.7, the CRDS–PLS FCIs' forecasting model generally outperforms the benchmark forecasting model in the stable period pre-2008-crisis, namely the continuous four out-of-sample intervals ranging from 03M7 through 07M6 pre-2008 crisis.

Similar to Chapter 4, the stable period is defined through a cross-economy investigation of its opposite—the identification of unstable period. Specifically, the CRDS–PLS FCIs' forecasting model slightly underperforms for the 00M7–01M6 out-of-sample interval with respect to Singapore and Taiwan, for the 01M7–02M6 out-of-sample interval with respect to Korea, and for the 02M7–03M6 out-of-sample interval with respect to Korea and Taiwan. The identification of unstable out-of-sample intervals are also supported from Figure 5.1 to Figure 5.4, where moderate shifts (not as strong as those large shifts during 2008 crisis) of CRDS–PLS FCIs occur with respect to the out-of-sample intervals, corresponding to the economies mentioned above. Further, this finding strengthens the postulation made in Chapter 4—the prolonged effect of the ACC (see Chapter 4) causes the location shift of FCIs in the 00M7–02M6 out-of-sample intervals with respect to the three economies, and China's entry into the WTO in 2002 can be another reason for the slight location shift of RDS–PLS FCIs in the 02M7–03M6 out-of- sample interval.

Unlike the three more developed economies, for Thailand, the general forecasting failure of RDS–PLS FCIs is observed, a result similar to those for CSDS–PLS FCIs in Chapter 4. It enhances the conclusion made in Chapter 4 that the in-sample model estimation failure—neither the level CRDS–PLS FCIs nor the CSDS–PLS FCIs survived in any round pre-2008 crisis—reflects a more remote link to the world trade of Thailand than that of the other three economies. As from Table 3, among all four target economies, the correlation coefficient between the import price index and CRDS–FCIs to Thailand is the lowest, as far as pre-2008 crisis subsample is concerned.

The CRDS–PLS vs. CSDS–PLS FCIs' forecasting model pre-2008 crisis

The predictive test of CRDS–PLS FCIs vs. CSDS–PLS FCIs forecasting models pre-2008 crisis is carried out here. The main findings are listed as follows.

1) The superiority of the CRDS–PLS FCIs over CSDS–PLS FCIs forecasting models is verified. With respect to the stable out-of-sample intervals, CRDS–PLS FCIs generally outperform the CSDS-PLS FCIs forecasting model.
2) With respect to the out-of-sample intervals pre-2008 crisis, for those unstable intervals that CRDS–PLS FCIs are inferior to the benchmark model, CRDS–PLS FCIs are also inferior to SDS–PLS FCIs; for the other stable out-of-sample intervals that CRDS–PLS FCIs outperform the benchmark forecasting model, CRDS–PLS FCIs also outperform CSDS–PLS FCIs.
3) The second finding corresponds well to the second postulation. For the unstable intervals, the inferiority of CRDS–PLS FCIs against CSDS–PLS FCIs results from a large-scale location shift in the level CRDS–PLS FCIs rather than a small-scaled one in the differenced CSDS–PLS FCIs; for those stable intervals, the fully exploited disaggregated dynamics contributes to the superiority of RDS–PLS FCIs against SDS–PLS FCIs.

A further investigation on forecasting horizons of stable out-of-sample intervals verifies the first postulation. Specifically, from the record of CRRMSE setting at 07M6 in Figure 5.5, an obvious downward trend of CRRMSE of RDS–PLS FCIs is observed, compared to the SDS–PLS FCIs forecasting model with respect to Singapore, Korea, and Taiwan.

RDS–PLS vs. both SDS–PLS and the benchmark forecasting model post-2008 crisis

In addition, the predictive tests of the CRDS–PLS FCIs vs. both the CSDS–PLS FCIs and the benchmark model are carried out post-2008 crisis as well. As a result, for all four target economies,

1) CRDS–PLS FCIs outperform CSDS–PLS FCIs forecasting models, the latter of which outperform the benchmark model for the 10M7–11M6 interval.
2) CRDS–PLS FCIs slightly underperform CSDS–PLS FCIs, the latter of which again slightly underperform the benchmark model for the other four intervals.

In a word, the findings from the predictive tests pre-2008 crisis and post-2008 crisis show that CRDS–PLS FCIs outperform CSDS–PLS FCIs, the latter of which outperform the benchmark in a stable period.

In addition to these empirical results, the comparison between the scale of the forecasting failures of FCIs pre-2008 crisis and post-2008 crisis finds larger-scale significant forecasting failures post-2008 crisis (rather than the pre-2008 crisis interval) in the case of Singapore, Korea, and Taiwan (judging by SRRMSE[110]). This finding can be explained by location shift as well. The location shift of FCIs in the unstable intervals post-2008 crisis is at a larger scale than that pre-2008 crisis. The location shift at different scales concurs with the economic shocks at different scales. First, the economic shocks may not be fully passed through into the CRDS–PLS FCIs in the period of the pre-2008 crisis. For example, some domestic financial indicators, such as those from Korea and Thailand, should be much susceptible to the prolonged ACC effect but are not included in the external financial indicator set, which are used to construct the FCIs. Second, Singapore, Korea, and Taiwan are more closely linked to the world trade than Thailand. In this sense, for the former three economies, the location shift is at a larger scale (than Thailand) due to the unprecedented (in terms of depth and scale) 2008 crisis than those from pre-2008 crisis.

5.5 Empirical results II

This section carries out the disaggregate analysis. Specifically, it evaluates the constancy at the disaggregate level from the dynamic forms in the parsimonious FDL models.

The general findings are as follows.

1) Weight estimates of CRDS–PLS FCIs are different from those of PLS-R and SDS–PLS. From Tables 5.8–5.11, in the context of the CRDS–PLS method, most of indicators are in the differenced form, while only a few indicators are in the level form. By contrast, both PLS-R and CSDS–PLS methods only allow level indicators to survive.
2) In addition to the first finding, in the context of RDS, the differenced indicators are not differenced at a unique frequency. In fact, they are either 1-month differenced or 2-month differenced. By contrast, (1) PLS-R can only reflect synchronized, differenced indicators of unique frequency. For example, $\Delta_2 f_{t-1}^{PLS}$ survived in the final forecasting model, reflecting synchronized, differenced disaggregated indicators of 2-month unique frequency; and (2) SDS–-PLS relaxes the synchronized restriction

[110] The empirical results show that SRRMSE of CRDS–PLS FCIs regarding unstable out-of-sample intervals pre-2008 crisis is much smaller than that post-2008 crisis, that is, $SRRMSE_{post-2008-crisis} \gg SRRMSE_{pre-2008-crisis} > 1$; while SRRMSE of CSDS–PLS FCIs with respect to unstable out-of-sample intervals pre-2008 crisis is larger than that post-2008 crisis, namely, a result that contradicts to the second postulation.

but still assumes a differenced indicator at a unique frequency. For example, $\Delta_4 f_{t-4}^{SDS-PLS}$ survived in the final forecasting model assumes differenced indicators with 4-month unique frequency.

3) Due to the fact that RDS–PLS allows financial indicators of all lags to drop out, much fewer indicators are found to be of explanatory power for Thailand than for the other three economies, which again signals the remote link between Thailand's macro economy and the external financial market.

5.5.1 Evaluating the constancy of disaggregate dynamic forms

This subsection selects two representative unstable out-of-sample intervals, respectively, pre-2008 crisis and within-2008 crisis to explore the non-constancy. The first out-of-sample interval is selected as the representative pre-2008 crisis for Singapore, Taiwan, and Thailand, and a second out-of-sample interval for Korea; 07M7–08M6 is selected to be the representative during the 2008 crisis regarding all four economies. From Table 5.5 to Table 5.12, non-constant indicators are observed in these two unstable out-of-sample intervals. The criteria for judging the constancy of weight estimators are:

1) The shift within the differenced form, such as from low frequency 5-month to 1-month differenced;
2) The shift in lag in the level form, such as from 5-month lag to 1-month lag in the level form;
3) The shift from differenced to level form or reversed shift;

The survival or dropping out of lagged indicators.

Before a further discussion on the constancy of weight estimators with respect to different target economies, two general findings can be summarized.

- Many more indicators experience weight shifts during the 2008 crisis rather than those in the pre-2008 crisis period.
- The non-constant indicators cluster either geographically or in specific types of market misalignment.

Singapore

- For the unstable interval pre-2008 crisis, the non-constant indicators from the US dominate compared to non-constant indicators from Japan (5 to 2, respectively). The common feature among these non-constant indicators is a transformation from high frequency into low frequency, such as high frequency differencing to low frequency differencing of the covered interest parity indicator from Japan and the equity–commodity price ratio from US, as well as the banking sector indicator from US, the dynamic form of which transforms from the differenced form into the level form.

- For the unstable interval during the 2008 crisis, the non-constant indicators are clustered with respect to the bond–equity ratios and market–inflation ratios. Geographical cluster is also observed: 75% (15/20) are US and Japanese indicators of all non-constant indicators, in contrast to the proportion of US and Japanese indicators ($\frac{22}{35} \approx 62\%$) in total indicators.

Korea

- For the unstable interval pre-2008 crisis, the number of non-constant indicators is mostly found from the US and UK (5 and 3, respectively).
- For the unstable interval during the 2008 crisis, in addition to that found in the Singapore case, extra cluster is observed regarding market misalignment (1) between long-term government bond and short-term T-bill (henceforth, GOV), namely, GOV of Japan (X10) and GOV of US (X12); and (2) of short-term market rate net of T-Bill rate (henceforth, TED), namely, TED of UK, TED of US.

Taiwan

- For the unstable interval pre-2008 crisis, more indicators are found to be non-constant than those in the cases of Singapore and Korea. Clusters are found in two types of market misalignment—equity–commodity price ratios and the derivative indicators.
- For the unstable interval during the 2008 crisis, cluster is found to be similar with that for Korea, namely the yield structures of bond market, TED indicators, and money–inflation rate ratios.

Thailand

- Shifts are observed in the level form, that is, the second and third type of shifts in survival form, are rarely seen because indicators in the level form rarely survive.

5.5.2 Leading role of financials

Investigation on the leading role of financial indicators is also divided by 2008 crisis in order to make it comparable to the findings at the disaggregate level with those in Chapter 4. Since at the aggregate level, CRDS–PLS FCIs have positive predictive power only regarding those stable out-of-sample intervals, the two out-of-sample intervals discussed previously are not reserved in the following analysis.

From Table 5.5 to Table 5.13, the types of market misalignment and individual indicators that contribute more significant predictive power to aggregated CRDS–PLS FCIs are extracted. When majority indicators survive within a market misalignment type, the market misalignment type is marked as a 'more significant' type in the upper body of Table 5.13. The lower body of Table 13 lists the 'more significant' indicators. Indicators are marked as 'more significant' when (1) they are in the differenced form with coefficient larger than 0.01[112], or (2) they are survived in the level form and survived in most of updating rounds, which are recorded from Table 5.8 to Table 5.11.

In general, several findings are found from Table 5.13.

- The superiority of derivative indicators. The two derivative indicators are constant, much leading in terms of the lag length and consistently survived in the level form.
- The yield structures of the money market only have marginal contribution both pre-2008 crisis and post-2008 crisis.
- The mixed form (level and differenced) of TED spread significantly survives both the pre-2008 crisis and post-2008 crisis intervals.
- Housing–equity price ratios significantly survive in the differenced form post-2008 crisis, in contrast to their insignificant survival pre-2008 crisis. It is postulated here that the investment transmission between real estate and the equity market has a more direct impact on the import price index of the three target economies post-2008 crisis than pre-2008 crisis.

As to each target economy, the main findings are as follow.

Singapore

- The more significant indicators are more diversified post-2008 crisis than pre-2008 crisis. For example, two out of three ECPI indicators (ECPI_R_JP, ECIP_R_UK), which are the ratio of equity price over the Consumer Price index, have much higher weights in the differenced form post-2008 crisis than pre-2008 crisis.

[112] Since indicators are standardized in each update, the absolute value of weight can represent their proportion to the construction of aggregate FCIs.

- Derivative indicators survive in the level form both pre-2008 crisis and post-2008 crisis. They are around 4–6 month leading.

Korea

- Money–bond interest rate ratios are significantly survived in the level form post-2008 crisis. The survived level indicators may be to a large extent responsible for their much larger forecasting failure post-2008 crisis than that of Singapore, due to the location shift.

Taiwan

- The findings are identical to those in the case of Korea.

Thailand

- Two indicators are found with much more significant dynamic forms post-2008 crisis. The banking sector indicator of the US and money–inflation rate of the US. Both indicators are survived in the differenced form but are very non-constant. For example, the banking sector indicator of the US is quite significant (around 0.04) in the 09M7–10M6 and 11M7–12M6 intervals but much more insignificant in the two intervals post-2008 crisis. In fact, the banking sector indicator of the US is suspected to be misspecified, as the intervals that it survives are those that the aggregate RDS–PLS FCIs are inferior to in comparison to the benchmark model.

5.6 Conclusion

This chapter modifies PLS-R by a Revised Dynamic Sparse method, namely the RDS–PLS method. The modelling of the disaggregate dynamics by RDS–PLS is equivalent to a parsimonious FDL regression model with the target regressed on each financial indicator. This method can model the disaggregate dynamics much more effectively than SDS–PLS, in the sense that RDS–PLS allows any form of lags to survival, or even all lags to drop out for any indicator, while SDS–PLS only allows a single lag in the level form to survive for each indicator.

This chapter only compares the first CRDS–PLS factor[114] with the first CSDS–PLS factor for two reasons. First, as this chapter theoretically proves, when the first three CSDS–PLS factors enter into the final forecasting model, if the weight estimate of one of the indicators is biased in the

[114] The factors are denoted as CRDS–PLS instead of RDS–PLS because the concatenation method is also used in this chapter, in the same way as for CSDS–PLS.

first CSDS–PLS factor, the bias is inherited in the second and third CSDS–PLS factors. Second, in the context of a single 'merged' FCI, the disaggregate analysis lacks statistical power.

Based on the modified experimental design, the important empirical findings are listed as follows:

- CRDS–PLS FCIs generally outperform CSDS–PLS FCIs and the benchmark model. The inferior forecasting performance of CRDS–PLS FCIs for a few out-of-sample intervals is due to location shift. Specifically, Chapter 4 showed that among a few out-of-sample intervals that CSDS–PLS FCIs fail to improve the forecasting performance, as a large location shift of CSDS–PLS FCIs has occurred. This chapter finds that it is exactly the same intervals that CRDS–PLS FCIs underperform the CSDS–PLS FCIs and the benchmark model. This is because differenced CSDS–PLS FCIs[115] that survived in-sample can largely difference out the location shift, while the level CRDS–PLS FCIs survived in-sample cannot.
- The only exception is Thailand, similar to the findings in Chapters 2, 3, and 4. Because the CRDS–PLS method allows the financial indicators to drop out in the CRDS–PLS FCIs, this chapter also finds there are far less indicators with significant weight estimates. The repeated forecasting failure, both at the aggregate and disaggregate levels, again strengthens the postulation that the import price index of Thailand has a much more remote link to external financial markets.

In addition to the findings discussed earlier, this chapter has other important findings at the disaggregate level:

- First and most importantly, the surviving dynamic forms of the same indicator vary as the target economy varies, in addition to the fact that the leading degree and weight estimates (Chapter 4) vary as the target economy varies. For example, money–bond interest rate ratios significantly survive in the level form with respect to Korea and Taiwan, but these indicators survived insignificantly in the differenced form for Singapore.
- Corroborating a finding in Chapter 4, it is shown that derivative Indicators significantly survive in the level form, are constant and leading above the average.

[115] Note that the CSDS–PLS FCIs adopted in this chapter are only the first CSDS–PLS FCIs issued, and they survive at level in the differenced form, while the first three CSDS–PLS FCIs were all allowed to be used in Chapter 3 and they survived in a mix of level and differenced forms.

- There are several findings that contradict those in Chapter 4: (1) the TED spread both in the level form and in the differenced form significantly survive both pre-2008 crisis and post-2008 crisis, a finding contradictory to one in Chapter 4, but corroborates another in Chapter 3; and (2) although housing–equity price ratios significantly survived post-2008 crisis, they survived in the differenced form.

Table 5.1 Weights constancy statistics

	Singapore	Thailand	Korea	Taiwan
1st	0.037	0.035	0.033	0.030
2nd	0.048	0.043	0.050	0.049
3rd	0.091	0.057	0.072	0.078

Table 5.2 The surviving forms of CRDS–PLS and CSDS–PLS FCIs

RDS	00M6	01M6	02M6	03M6-07M6	08M6	09M6	10M6	11M6	12M6
SG	$\Delta_2 f_t^{RDS}$	$\Delta_2 f_t^{RDS}$ f_{t-6}^{RDS}	~	~	~	~	$\Delta_2 f_t^{RDS}$	$\Delta_2 f_t^{RDS}$	$\Delta_2 f_t^{RDS}$
TH	$\Delta_2 f_t^{RDS}$	~	~	~	~	~	~	~	~
KOR	Δf_t^{RDS} f_{t-1}^{RDS}	~	~	~	~	~	~	~	~
TW	f_t^{RDS}	~	Δf_t^{RDS} f_t^{RDS}	~	~	~	~	~	~
SDS	00M6	01M6	02M6	03M6-07M6	08M6	09M6	10M6	11M6	12M6
SG	Δf_{t-1}^{SDS} $\Delta_4 f_{t-4}^{SDS}$	~	~	~	$\Delta_2 f_{t-1}^{SDS}$ $\Delta_4 f_{t-2}^{SDS}$	~	~	~	~
TH	$\Delta_2 f_t^{SDS}$	~	~	~	~	~	~	~	~
KOR	Δf_t^{SDS}	~	~	~	~	~	~	~	~
TW	$\Delta_3 f_t^{SDS}$	~	~	~	~	Δf_t^{SDS}	~	~	~

Note: the tilde sign '~' refers to the unchanged form of FCIs at the last update.

Table 5.3 Correlation between the import price index and the concatenated RDS–FCIs at the intervals pre-2008 crisis

	00M6	01M6	02M6	03M6	04M6	05M6	06M6	07M6
SG	0.48	0.48	0.49	0.48	0.47	0.47	0.46	0.41
KOR	0.60	0.54	0.54	0.58	0.57	0.55	0.53	0.32
TW	0.58	0.58	0.55	0.58	0.57	0.55	0.54	0.45
TH	0.35	0.39	0.37	0.36	0.39	0.38	0.37	0.30

Table 5.4 Singapore: Out-of-sample encompassing test results

CRDS–PLS vs. CSDS–PLS													
	00M7–01M6	01M7–02M6	02M7–03M6	03M7–04M6	04M7–05M6	05M7–06M6	06M7–07M6	07M7–08M6	08M7–09M6	09M7–10M6	10M7–11M6	11M7–12M6	12M7–13M6
SRRMSE (P-SRRMSE)	0.962 (0.573)	1.008 (0.333)	0.97 (0.734)	0.927 (0.541)	0.937 (0.721)	0.971 (0.703)	1.003 (0.393)	1.027 (0.181)	1.008 (0.264)	1.033 (0.17)	0.95 (0.798)	1.022 (0.192)	1.026 (0.146)
	1.032 (0.263)	1.011 (0.359)	0.914 (0.801)	0.738 (0.928)	0.875 (0.885)	0.952 (0.816)	1.009 (0.356)	1.02 (0.198)	1.01 (0.227)	1.045 (0.154)	0.953 (0.773)	1.02 (0.161)	1.026 (0.166)
	1.055 (0.193)	1.01 (0.391)	0.876 (0.752)	0.71 (0.953)	0.814 (0.948)	0.924 (0.86)	1.019 (0.314)	1.01 (0.307)	1.013 (0.179)	1.029 (0.309)	0.962 (0.739)	1.021 (0.195)	1.022 (0.193)
	1.075 (0.174)	1.011 (0.397)	0.856 (0.684)	0.676 (0.961)	0.763 (0.993)	0.895 (0.89)	1.024 (0.35)	1.008 (0.375)	1.016 (0.133)	1.006 (0.37)	0.968 (0.729)	1.016 (0.291)	1.027 (0.209)
	1.086 (0.202)	1.029 (0.375)	0.711 (0.786)	0.667 (0.931)	0.725 (0.999)	0.877 (0.88)	1.012 (0.43)	1.006 (0.431)	1.019 (0.18)	0.984 (0.392)	0.969 (0.721)	0.998 (0.505)	1.085 (0.22)
	1.076 (0.349)	1.058 (0.418)	0.694 (0.662)	0.651 (0.883)	0.727 (0.921)	0.865 (0.785)	1.018 (0.464)	1.007 (0.464)	1.022 (0.32)	0.946 (0.47)	0.971 (0.659)	0.951 (0.629)	1.082 (0.37)
CRRMSE (P-CRRMSE)	0.956 (0.573)	0.986 (0.396)	0.991 (0.497)	0.979 (0.52)	0.971 (0.647)	0.97 (0.743)	0.975 (0.708)	0.986 (0.501)	0.996 (0.341)	0.999 (0.232)	0.997 (0.341)	0.999 (0.244)	0.999 (0.189)
	1.032 (0.263)	1.017 (0.24)	0.998 (0.368)	0.973 (0.559)	0.955 (0.768)	0.954 (0.888)	0.961 (0.861)	0.977 (0.706)	0.995 (0.42)	0.997 (0.322)	0.993 (0.463)	0.996 (0.365)	0.998 (0.296)
	1.055 (0.193)	1.023 (0.22)	1.003 (0.319)	0.964 (0.608)	0.935 (0.877)	0.932 (0.96)	0.941 (0.944)	0.965 (0.877)	0.994 (0.481)	0.994 (0.417)	0.992 (0.554)	0.994 (0.476)	0.995 (0.43)
	1.075 (0.174)	1.031 (0.182)	1.01 (0.259)	0.96 (0.626)	0.92 (0.941)	0.913 (0.989)	0.923 (0.981)	0.957 (0.948)	0.994 (0.494)	0.994 (0.442)	0.991 (0.588)	0.992 (0.543)	0.993 (0.515)
	1.086 (0.202)	1.049 (0.133)	1.02 (0.209)	0.954 (0.639)	0.91 (0.939)	0.9 (0.992)	0.909 (0.989)	0.951 (0.972)	0.992 (0.544)	0.992 (0.501)	0.989 (0.654)	0.99 (0.655)	0.99 (0.62)
	1.076 (0.349)	1.066 (0.134)	1.025 (0.22)	0.942 (0.687)	0.897 (0.94)	0.887 (0.995)	0.895 (0.993)	0.943 (0.981)	0.989 (0.621)	0.988 (0.591)	0.986 (0.731)	0.986 (0.75)	0.986 (0.721)

RDS vs. benchmark													
SRRMSE (P-SRRMSE)	1.107 (.063*)	0.967 (0.704)	0.991 (0.486)	1.007 (0.245)	0.953 (0.697)	0.968 (0.713)	0.984 (0.575)	1.058 (0.106)	1.013 (0.1)	1.039 (0.092*)	0.959 (0.712)	1.028 (0.177)	1.051 (0.112)
	1.228 (.037**)	0.965 (0.762)	0.915 (0.857)	0.799 (0.827)	0.906 (0.844)	0.959 (0.739)	0.983 (0.566)	1.051 (0.113)	1.018 (0.079*)	1.066 (0.055*)	0.957 (0.749)	1.028 (0.129)	1.044 (0.163)
	1.318 (.016**)	0.964 (0.737)	0.901 (0.679)	0.787 (0.865)	0.852 (0.926)	0.937 (0.793)	0.987 (0.498)	1.041 (0.118)	1.022 (0.078*)	1.073 (0.216)	0.968 (0.711)	1.037 (0.182)	1.031 (0.252)
	1.328 (.024**)	0.968 (0.632)	0.887 (0.613)	0.768 (0.876)	0.803 (0.987)	0.905 (0.862)	0.977 (0.516)	1.047 (0.064*)	1.027 (0.091*)	1.07 (0.217)	0.978 (0.671)	1.041 (0.275)	1.011 (0.39)
	1.343 (0.107)	0.989 (0.496)	0.762 (0.668)	0.765 (0.862)	0.77 (0.995)	0.884 (0.877)	0.966 (0.529)	1.055 (0.068*)	1.034 (0.142)	1.073 (0.239)	0.981 (0.644)	1.015 (0.436)	1.018 (0.409)
	1.343 (0.292)	1.026 (0.446)	0.772 (0.606)	0.746 (0.835)	0.775 (0.919)	0.868 (0.796)	0.973 (0.499)	1.06 (0.224)	1.044 (0.293)	1.052 (0.442)	0.983 (0.579)	0.946 (0.549)	1.024 (0.456)
CRRMSE (P-CRRMSE)	0.956 (0.573)	0.986 (0.396)	0.991 (0.497)	0.979 (0.52)	0.971 (0.647)	0.97 (0.743)	0.975 (0.708)	0.986 (0.501)	0.996 (0.341)	0.999 (0.232)	0.997 (0.341)	0.999 (0.244)	0.999 (0.189)
	1.032 (0.263)	1.017 (0.24)	0.998 (0.368)	0.973 (0.559)	0.955 (0.768)	0.954 (0.888)	0.961 (0.861)	0.977 (0.706)	0.995 (0.42)	0.997 (0.322)	0.993 (0.463)	0.996 (0.365)	0.998 (0.296)
	1.055 (0.193)	1.023 (0.22)	1.003 (0.319)	0.964 (0.608)	0.935 (0.877)	0.932 (0.96)	0.941 (0.944)	0.965 (0.877)	0.994 (0.481)	0.994 (0.417)	0.992 (0.554)	0.994 (0.476)	0.995 (0.43)
	1.075 (0.174)	1.031 (0.182)	1.01 (0.259)	0.96 (0.626)	0.92 (0.941)	0.913 (0.989)	0.923 (0.981)	0.957 (0.948)	0.994 (0.494)	0.994 (0.442)	0.991 (0.588)	0.992 (0.543)	0.993 (0.515)
	1.086 (0.202)	1.049 (0.133)	1.02 (0.209)	0.954 (0.639)	0.91 (0.939)	0.9 (0.992)	0.909 (0.989)	0.951 (0.972)	0.992 (0.544)	0.992 (0.501)	0.989 (0.654)	0.99 (0.655)	0.99 (0.62)
	1.076 (0.349)	1.066 (0.134)	1.025 (0.22)	0.942 (0.687)	0.897 (0.94)	0.887 (0.995)	0.895 (0.993)	0.943 (0.981)	0.989 (0.621)	0.988 (0.591)	0.986 (0.731)	0.986 (0.75)	0.986 (0.721)

Table 5.5 Korea: Out-of-sample encompassing test results

CRDS–PLS vs. CSDS–PLS													
	00M7–01M6	01M7–02M6	02M7–03M6	03M7–04M6	04M7–05M6	05M7–06M6	06M7–07M6	07M7–08M6	08M7–09M6	09M7–10M6	10M7–11M6	11M7–12M6	12M7–13M6
SRRMSE (P-SRRMSE)	0.955 (0.73)	1.088 (.049**)	0.983 (0.665)	0.902 (0.662)	0.924 (0.892)	0.983 (0.428)	0.985 (0.413)	1.436 (.003**)	1.022 (0.079*)	1.152 (.023**)	0.818 (0.864)	1.02 (0.184)	1.141 (0.096*)
	0.979 (0.458)	1.101 (0.078*)	0.987 (0.61)	0.774 (0.919)	0.916 (0.873)	0.998 (0.366)	1.091 (0.111)	1.484 (.003**)	1.013 (0.183)	1.025 (0.201)	0.685 (0.996)	1.077 (0.167)	1.167 (0.089*)
	1.019 (0.304)	1.081 (0.053*)	1.02 (0.19)	0.67 (0.943)	0.895 (0.899)	1.008 (0.333)	1.163 (0.065*)	1.505 (.007**)	1.011 (0.12)	0.919 (0.517)	0.626 (0.998)	1.107 (0.162)	1.179 (0.091*)
	0.983 (0.47)	1.086 (.031**)	1.053 (0.198)	0.697 (0.952)	0.894 (0.921)	0.975 (0.374)	1.192 (0.077*)	1.518 (.017**)	1.009 (0.125)	0.859 (0.713)	0.598 (0.997)	1.141 (0.201)	1.428 (0.066*)
	0.987 (0.482)	1.084 (0.105)	1.109 (0.215)	0.689 (0.918)	0.87 (0.867)	0.938 (0.46)	1.155 (0.154)	1.535 (.047**)	1.01 (0.271)	0.693 (0.832)	0.602 (0.991)	1.181 (0.27)	1.76 (0.102)
	0.939 (0.559)	1.088 (0.281)	1.055 (0.393)	0.693 (0.898)	0.849 (0.788)	0.892 (0.529)	1.139 (0.339)	1.559 (0.185)	1.018 (0.318)	0.761 (0.585)	0.595 (0.937)	1.554 (0.31)	1.725 (0.297)
CRRMSE (P-CRRMSE)	0.974 (0.73)	1.004 (0.164)	1.001 (0.233)	0.984 (0.391)	0.964 (0.798)	0.964 (0.729)	0.969 (0.695)	1.041 (.024**)	1.034 (.013**)	1.046 (.003**)	1.038 (.005**)	1.035 (.003**)	1.041 (.001**)
	0.979 (0.458)	1.052 (0.072*)	1.018 (0.115)	0.993 (0.317)	0.971 (0.677)	0.977 (0.507)	0.991 (0.282)	1.114 (.004**)	1.075 (.003**)	1.072 (.002**)	1.056 (.005**)	1.057 (.003**)	1.062 (.001**)
	1.019 (0.304)	1.063 (.029**)	1.043 (.011**)	0.997 (0.257)	0.969 (0.698)	0.977 (0.467)	1 (0.17)	1.166 (.004**)	1.1 (.003**)	1.095 (.003**)	1.071 (.008**)	1.073 (.005**)	1.077 (.002**)
	0.983 (0.47)	1.058 (.028**)	1.056 (.008**)	0.993 (0.321)	0.958 (0.828)	0.96 (0.672)	0.987 (0.297)	1.188 (.007**)	1.111 (.005**)	1.104 (.006**)	1.074 (.015**)	1.077 (0.01**)	1.083 (.005**)
	0.987 (0.482)	1.057 (0.064*)	1.068 (.012**)	0.978 (0.481)	0.941 (0.879)	0.94 (0.803)	0.966 (0.517)	1.209 (.012**)	1.123 (.009**)	1.114 (.011**)	1.077 (.026**)	1.079 (.019**)	1.087 (.011**)
	0.939 (0.559)	1.031 (0.269)	1.036 (0.151)	0.928 (0.844)	0.897 (0.987)	0.896 (0.982)	0.919 (0.929)	1.195 (.026**)	1.126 (.02**)	1.115 (.022**)	1.072 (.049**)	1.076 (.037**)	1.084 (.023**)

RDS vs. benchmark													
SRRMSE (P-SRRMSE)	0.969 (0.662)	1.097 (0.07*)	0.987 (0.555)	0.913 (0.6)	0.927 (0.909)	0.994 (0.388)	0.978 (0.477)	1.464 (.002**)	1.032 (0.04**)	1.141 (.043**)	0.804 (0.878)	1.033 (0.166)	1.143 (0.107)
	0.963 (0.648)	1.061 (0.084*)	0.996 (0.44)	0.768 (0.858)	0.921 (0.882)	1.007 (0.341)	1.079 (0.123)	1.496 (.003**)	1.023 (.048**)	0.968 (0.345)	0.668 (0.997)	1.09 (0.161)	1.178 (0.097*)
	0.97 (0.506)	1.05 (0.072*)	1.033 (0.066*)	0.652 (0.913)	0.907 (0.881)	1.019 (0.31)	1.143 (0.074*)	1.511 (.005**)	1.016 (0.068*)	0.841 (0.6)	0.611 (0.998)	1.119 (0.166)	1.185 (0.103)
	0.903 (0.704)	1.046 (0.225)	1.063 (0.161)	0.681 (0.931)	0.908 (0.909)	0.997 (0.339)	1.168 (0.084*)	1.526 (.013**)	1.014 (0.089*)	0.774 (0.781)	0.585 (0.996)	1.152 (0.206)	1.457 (0.07*)
	0.887 (0.708)	1.048 (0.33)	1.167 (0.174)	0.671 (0.912)	0.898 (0.829)	0.959 (0.432)	1.139 (0.151)	1.546 (.039**)	1.016 (0.153)	0.602 (0.865)	0.589 (0.989)	1.18 (0.274)	1.822 (0.104)
	0.844 (0.647)	1.072 (0.424)	1.19 (0.338)	0.675 (0.898)	0.883 (0.74)	0.912 (0.521)	1.139 (0.335)	1.572 (0.173)	1.022 (0.306)	0.68 (0.599)	0.582 (0.93)	1.55 (0.317)	1.775 (0.299)
CRRMSE (P-CRRMSE)	1.007 (0.662)	1.019 (0.114)	1.01 (0.16)	0.992 (0.263)	0.97 (0.703)	0.971 (0.625)	0.974 (0.611)	1.049 (.016**)	1.043 (.006**)	1.052 (.001**)	1.043 (.003**)	1.041 (.002**)	1.047 (.001**)
	0.963 (0.648)	1.023 (0.126)	1.009 (0.15)	0.984 (0.391)	0.966 (0.741)	0.975 (0.534)	0.988 (0.315)	1.114 (.004**)	1.078 (.002**)	1.073 (.002**)	1.055 (.005**)	1.057 (.003**)	1.062 (.001**)
	0.97 (0.506)	1.026 (0.128)	1.029 (.027**)	0.982 (0.375)	0.962 (0.742)	0.974 (0.487)	0.995 (0.202)	1.163 (.004**)	1.101 (.002**)	1.093 (.003**)	1.067 (.008**)	1.07 (.004**)	1.074 (.002**)
	0.903 (0.704)	1.006 (0.332)	1.026 (0.123)	0.966 (0.568)	0.946 (0.887)	0.954 (0.737)	0.978 (0.401)	1.184 (.007**)	1.111 (.005**)	1.1 (.006**)	1.069 (.016**)	1.072 (0.01**)	1.078 (.005**)
	0.887 (0.708)	1 (0.405)	1.031 (0.167)	0.946 (0.662)	0.931 (0.893)	0.936 (0.816)	0.961 (0.578)	1.208 (.011**)	1.126 (.008**)	1.111 (0.01**)	1.073 (.026**)	1.075 (.019**)	1.083 (0.01**)
	0.844 (0.647)	0.976 (0.512)	1.012 (0.339)	0.905 (0.819)	0.897 (0.964)	0.9 (0.96)	0.922 (0.891)	1.202 (.023**)	1.132 (.017**)	1.115 (.021**)	1.069 (.047**)	1.073 (.035**)	1.082 (.021**)

Table 5.6 Taiwan: Out-of-sample encompassing test results

RDS vs. SDS													
	00M7─01M6	01M7─02M6	02M7─03M6	03M7─04M6	04M7─05M6	05M7─06M6	06M7─07M6	07M7─08M6	08M7─09M6	09M7─10M6	10M7─11M6	11M7─12M6	12M7─13M6
SRRMSE (P-SRRMSE)	1.026 (0.2)	1.019 (0.315)	1.033 (0.126)	0.767 (0.514)	0.942 (0.129)	0.909 (0.588)	0.994 (0.371)	1.152 (.012**)	1.042 (0.212)	1.082 (0.142)	0.889 (0.68)	1.217 (.044**)	1.205 (.013**)
	1.33 (.049**)	1.032 (0.263)	1.033 (0.149)	0.665 (0.66)	0.964 (0.095*)	0.855 (0.7)	1.008 (0.26)	1.226 (.013**)	1.083 (0.138)	1.115 (0.077*)	0.732 (0.978)	1.234 (.031**)	1.233 (.021**)
	1.624 (.015**)	1.018 (0.362)	1.056 (0.175)	0.549 (0.784)	0.921 (0.085*)	0.785 (0.734)	1.001 (0.297)	1.189 (.033**)	1.128 (0.106)	1.145 (0.148)	0.641 (0.995)	1.274 (.042**)	1.326 (.033**)
	1.62 (0.02**)	0.996 (0.465)	1.033 (0.222)	0.512 (0.819)	0.827 (0.1)	0.729 (0.688)	0.979 (0.36)	1.185 (0.076*)	1.143 (0.124)	1.114 (0.15)	0.631 (0.991)	1.364 (.044**)	1.536 (.032**)
	1.539 (0.089*)	0.996 (0.471)	0.881 (0.307)	0.467 (0.85)	0.94 (0.06*)	0.709 (0.643)	0.965 (0.413)	1.181 (0.159)	1.137 (0.197)	1.14 (0.136)	0.621 (0.978)	1.659 (0.08*)	1.742 (0.056*)
	1.5 (0.266)	1.005 (0.475)	0.664 (0.41)	0.439 (0.771)	0.977 (0.1)	0.673 (0.589)	0.961 (0.458)	1.177 (0.301)	1.138 (0.347)	1.189 (0.331)	0.631 (0.871)	2.088 (0.143)	1.666 (0.212)
CRRMSE (P-CRRMSE)	0.986 (0.2)	1.027 (0.157)	1.012 (0.056*)	0.975 (0.078*)	0.968 (.032**)	0.953 (0.062*)	0.963 (0.057*)	0.992 (.011**)	1.014 (.025**)	1.022 (.012**)	1.012 (.016**)	1.025 (.005**)	1.034 (.001**)
	1.33 (.049**)	1.105 (.032**)	1.078 (.015**)	0.995 (.039**)	0.99 (0.01**)	0.949 (0.05*)	0.959 (.037**)	1.004 (.004**)	1.042 (.008**)	1.046 (.004**)	1.022 (0.01**)	1.037 (.003**)	1.047 (.001**)
	1.624 (.015**)	1.121 (.024**)	1.098 (.015**)	0.977 (0.056*)	0.971 (.013**)	0.916 (0.078*)	0.929 (0.058*)	0.984 (.009**)	1.054 (.006**)	1.056 (.004**)	1.021 (.013**)	1.039 (.004**)	1.053 (.001**)
	1.62 (0.02**)	1.097 (0.051*)	1.081 (.025**)	0.932 (0.131)	0.922 (.039**)	0.87 (0.145)	0.885 (0.118)	0.957 (.023**)	1.053 (.008**)	1.054 (.005**)	1.014 (0.02**)	1.032 (.006**)	1.048 (.001**)
	1.539 (0.089*)	1.109 (0.07*)	1.063 (.033**)	0.871 (0.277)	0.876 (0.071*)	0.826 (0.242)	0.843 (0.205)	0.929 (0.054*)	1.043 (.013**)	1.044 (.008**)	0.999 (.036**)	1.016 (.012**)	1.035 (.003**)
	1.5 (0.266)	1.153 (0.09*)	1.062 (.034**)	0.814 (0.447)	0.824 (0.137)	0.774 (0.405)	0.792 (0.352)	0.892 (0.129)	1.026 (.028**)	1.029 (.016**)	0.976 (0.078*)	0.994 (.033**)	1.012 (.011**)

RDS vs. benchmark													
SRRMSE (P-SRRMSE)	1.074 (0.098*)	1.012 (0.145)	0.978 (0.241)	0.854 (0.321)	0.983 (0.165)	0.954 (0.428)	0.954 (0.57)	1.315 (.019**)	1.022 (0.22)	1.063 (0.159)	0.856 (0.657)	1.203 (.027**)	1.156 (.013**)
	1.123 (0.094*)	0.967 (0.391)	1.028 (0.175)	0.736 (0.541)	0.963 (0.175)	0.89 (0.609)	0.951 (0.484)	1.461 (.011**)	1.063 (0.175)	1.066 (0.083*)	0.695 (0.961)	1.243 (.028**)	1.194 (.022**)
	1.113 (0.099*)	0.943 (0.453)	1.073 (0.203)	0.621 (0.642)	0.938 (0.134)	0.824 (0.663)	0.952 (0.428)	1.428 (.017**)	1.118 (0.143)	0.976 (0.119)	0.609 (0.993)	1.285 (0.05*)	1.313 (0.03**)
	1.033 (0.209)	0.924 (0.479)	1.1 (0.255)	0.565 (0.768)	0.94 (0.109)	0.764 (0.65)	0.921 (0.45)	1.439 (.036**)	1.183 (0.146)	0.91 (0.147)	0.605 (0.989)	1.388 (0.061*)	1.577 (.029**)
	0.974 (0.38)	0.922 (0.463)	1.025 (0.342)	0.507 (0.857)	1.298 (0.05*)	0.735 (0.632)	0.902 (0.461)	1.46 (0.09*)	1.23 (0.208)	0.847 (0.154)	0.603 (0.982)	1.645 (0.097*)	1.829 (0.051*)
	0.954 (0.476)	0.965 (0.455)	0.919 (0.422)	0.469 (0.801)	1.712 (0.107)	0.689 (0.59)	0.896 (0.472)	1.505 (0.251)	1.267 (0.351)	0.896 (0.329)	0.62 (0.908)	1.982 (0.135)	1.773 (0.212)
CRRMSE (P-CRRMSE)	1.104 (0.098*)	1.039 (0.04**)	1.002 (.032**)	0.985 (.029**)	0.985 (.015**)	0.978 (.022**)	0.975 (.035**)	1.02 (.003**)	1.021 (.041**)	1.026 (.024**)	1.013 (.029**)	1.025 (.013**)	1.032 (.007**)
	1.123 (0.094*)	1.01 (0.113)	1.016 (0.05*)	0.97 (0.069*)	0.969 (.033**)	0.947 (0.087*)	0.948 (0.096*)	1.016 (.006**)	1.039 (.033**)	1.041 (0.02**)	1.013 (.033**)	1.028 (.016**)	1.038 (.008**)
	1.113 (0.099*)	0.984 (0.191)	1.011 (0.088*)	0.945 (0.132)	0.944 (0.069*)	0.912 (0.164)	0.918 (0.155)	1.004 (0.01**)	1.061 (.021**)	1.059 (.014**)	1.018 (.029**)	1.037 (.014**)	1.05 (.006**)
	1.033 (0.209)	0.951 (0.311)	0.981 (0.167)	0.895 (0.279)	0.898 (0.172)	0.865 (0.293)	0.873 (0.278)	0.981 (.025**)	1.085 (.018**)	1.081 (.013**)	1.031 (.027**)	1.049 (.014**)	1.066 (.006**)
	0.974 (0.38)	0.938 (0.359)	0.95 (0.231)	0.835 (0.448)	0.855 (0.252)	0.821 (0.428)	0.832 (0.404)	0.956 (0.052*)	1.101 (.023**)	1.096 (.016**)	1.037 (.034**)	1.054 (0.02**)	1.074 (0.01**)
	0.954 (0.476)	0.96 (0.342)	0.956 (0.245)	0.792 (0.584)	0.818 (0.35)	0.777 (0.605)	0.789 (0.559)	0.931 (0.105)	1.106 (.035**)	1.102 (.024**)	1.031 (0.051*)	1.048 (.033**)	1.068 (.017**)

Table 5.7 Thailand: Out-of-sample encompassing test results

RDS vs. SDS													
Out-of-sample period	00M7–01M6	01M7–02M6	02M7–03M6	03M7–04M6	04M7–05M6	05M7–06M6	06M7–07M6	07M7–08M6	08M7–09M6	09M7–10M6	10M7–11M6	11M7–12M6	12M7–13M6
SRRMSE (P-SRRMSE)	0.904	0.638	0.859	1.232	0.837	1.093	0.987	1.043	0.872	1.219	0.939	1.25	1.172
	(0.115)	(0.683)	(0.8)	(0.061*)	(0.367)	(0.1)	(0.355)	(0.126)	(0.591)	(0.067*)	(0.819)	(0.054*)	(.024**)
	0.658	0.369	0.852	1.079	0.83	1.063	0.932	0.991	0.86	1.362	0.894	1.327	1.308
	(0.151)	(0.785)	(0.664)	(0.093*)	(0.882)	(0.115)	(0.669)	(0.325)	(0.712)	(.035**)	(0.986)	(.022**)	(.026**)
	0.563	0.513	0.873	0.963	0.772	1.032	0.928	0.976	0.835	1.632	0.871	1.475	1.336
	(0.243)	(0.624)	(0.646)	(0.343)	(0.997)	(0.232)	(0.742)	(0.526)	(0.782)	(.026**)	(0.996)	(.042**)	(0.083*)
	0.558	0.522	0.861	0.802	0.73	1.05	0.978	0.987	0.832	1.663	0.871	1.521	1.61
	(0.153)	(0.487)	(0.749)	(0.699)	(0.986)	(0.273)	(0.529)	(0.545)	(0.731)	(0.059*)	(0.995)	(0.04**)	(0.172)
	0.468	0.41	0.846	0.865	0.702	1.076	0.971	0.993	0.814	1.69	0.863	1.436	1.535
	(0.244)	(0.575)	(0.836)	(0.569)	(0.996)	(0.214)	(0.567)	(0.511)	(0.683)	(0.078*)	(0.973)	(0.12)	(0.18)
	0.574	0.335	0.828	0.997	0.665	1.038	0.901	0.987	0.762	1.663	0.862	1.586	1.85
	(0.397)	(0.566)	(0.777)	(0.457)	(0.989)	(0.393)	(0.603)	(0.516)	(0.622)	(0.205)	(0.865)	(0.373)	(0.266)
CRRMSE (P-CRRMSE)	0.859	0.819	0.829	0.915	0.912	0.951	0.963	0.98	0.958	0.965	0.962	0.969	0.971
	(0.115)	(0.124)	(0.179)	(0.053*)	(.049**)	(.026**)	(.023**)	(.011**)	(.023**)	(.018**)	(.019**)	(.014**)	(.012**)
	0.658	0.567	0.691	0.795	0.8	0.881	0.89	0.927	0.911	0.917	0.916	0.922	0.924
	(0.151)	(0.166)	(0.238)	(0.109)	(0.13)	(0.071*)	(0.095*)	(0.082*)	(0.26)	(0.214)	(0.252)	(0.198)	(0.182)
	0.563	0.545	0.704	0.769	0.769	0.851	0.864	0.916	0.894	0.901	0.899	0.904	0.905
	(0.243)	(0.242)	(0.329)	(0.275)	(0.408)	(0.336)	(0.412)	(0.458)	(0.759)	(0.693)	(0.755)	(0.706)	(0.687)
	0.558	0.547	0.72	0.74	0.738	0.823	0.847	0.922	0.898	0.906	0.903	0.907	0.908
	(0.153)	(0.105)	(0.229)	(0.332)	(0.588)	(0.45)	(0.463)	(0.524)	(0.804)	(0.733)	(0.799)	(0.763)	(0.746)
	0.468	0.45	0.675	0.722	0.717	0.804	0.826	0.922	0.895	0.903	0.901	0.903	0.904
	(0.244)	(0.184)	(0.428)	(0.498)	(0.812)	(0.67)	(0.694)	(0.64)	(0.856)	(0.792)	(0.854)	(0.837)	(0.824)
	0.574	0.479	0.69	0.77	0.744	0.811	0.821	0.923	0.888	0.896	0.894	0.895	0.896
	(0.397)	(0.306)	(0.571)	(0.498)	(0.828)	(0.783)	(0.839)	(0.766)	(0.931)	(0.891)	(0.935)	(0.931)	(0.925)

RDS vs. benchmark													
SRRMSE (P-SRRMSE)	1.063 (0.138)	0.722 (0.296)	0.808 (0.863)	1.281 (.049**)	1.281 (.025**)	1.351 (.035**)	1.257 (.012**)	1.503 (.002**)	1.172 (.049**)	1.11 (0.091*)	0.994 (0.399)	1.286 (.038**)	0.988 (0.37)
	1.132 (0.069*)	0.696 (0.332)	1.088 (0.065*)	1.241 (.018**)	1.353 (.028**)	1.338 (.018**)	1.224 (.016**)	1.463 (.017**)	1.208 (0.055*)	1.097 (0.109)	0.951 (0.652)	1.43 (.007**)	0.912 (0.55)
	1.193 (0.133)	0.941 (0.22)	1.166 (0.097*)	1.307 (0.058*)	1.29 (0.064*)	1.306 (.011**)	1.211 (0.081*)	1.497 (0.02**)	1.231 (0.05*)	1.095 (0.151)	0.919 (0.817)	1.589 (0.05*)	0.839 (0.841)
	1.27 (0.198)	0.948 (0.134)	1.169 (0.172)	1.224 (0.156)	1.235 (0.149)	1.319 (0.086*)	1.357 (0.103)	1.52 (.019**)	1.279 (0.057*)	1.1 (0.132)	0.903 (0.87)	1.544 (0.114)	0.812 (0.98)
	1.236 (0.244)	0.868 (0.28)	1.215 (0.228)	1.268 (0.249)	1.182 (0.255)	1.354 (0.186)	1.378 (0.14)	1.532 (.047**)	1.258 (0.157)	1.077 (0.241)	0.885 (0.851)	1.433 (0.22)	0.836 (0.807)
	1.104 (0.416)	0.846 (0.414)	1.2 (0.364)	1.3 (0.378)	1.11 (0.349)	1.294 (0.333)	1.323 (0.37)	1.522 (0.209)	1.159 (0.341)	1.076 (0.351)	0.88 (0.726)	1.553 (0.373)	0.801 (0.632)
CRRMSE (P-CRRMSE)	1.062 (0.138)	0.934 (0.102)	0.87 (0.398)	0.966 (0.064*)	0.982 (.028**)	1.049 (.004**)	1.086 (.001**)	1.167 (.001*)	1.168 (.001*)	1.167 (.001*)	1.155 (.001*)	1.159 (.001*)	1.155 (.001*)
	1.132 (0.069*)	1.008 (.048**)	1.053 (.008**)	1.12 (.001*)	1.149 (.001*)	1.215 (.001*)	1.217 (.001*)	1.301 (.001*)	1.278 (.001*)	1.273 (.001*)	1.247 (.001*)	1.251 (.001*)	1.246 (.001*)
	1.193 (0.133)	1.087 (0.063*)	1.137 (.012**)	1.188 (.001**)	1.206 (.001*)	1.244 (.001*)	1.238 (.001*)	1.351 (.001*)	1.319 (.001*)	1.313 (.001*)	1.277 (.001*)	1.28 (.001*)	1.275 (.001*)
	1.27 (0.198)	1.146 (0.053*)	1.162 (.022**)	1.178 (.005**)	1.191 (.001**)	1.236 (.001*)	1.256 (.001*)	1.394 (.001*)	1.364 (.001*)	1.356 (.001*)	1.309 (.001*)	1.311 (.001*)	1.306 (.001*)
	1.236 (0.244)	1.093 (0.062*)	1.184 (.036**)	1.21 (.009**)	1.203 (.003**)	1.252 (.001**)	1.271 (.001*)	1.421 (.001**)	1.381 (.001*)	1.37 (.001*)	1.317 (.001*)	1.318 (.001*)	1.312 (.001*)
	1.104 (0.416)	1.025 (0.17)	1.154 (0.066*)	1.203 (.019**)	1.182 (.008**)	1.215 (.001**)	1.228 (.001*)	1.406 (.003**)	1.352 (.001**)	1.343 (.001**)	1.286 (.002**)	1.287 (.001**)	1.283 (.001**)

Table 5.8 Singapore: Weights of disaggregate indicators

00M6		01M6		02M6		03M6		04M6		05M6		06M6		07M6		08M6		09M6		10M6		11M6		12M6	
X1(-2)	.017	X1(-2)	.017	X1(-2)	.017	X1(-2)	.017	X1(-2)	.017	X1(-2)	.017	X1(-2)	.017	X1(-2)	.017	X1(-2)	.015	X1(-2)	.017	X1(-2)	.017	X1(-2)	.016	X1(-2)	.016
X1(-4)	-.013	X1(-4)	-.013	X1(-4)	-.014	X1(-4)	-.014	X1(-4)	-.015	X1(-4)	-.014	X1(-4)	-.015	X1(-4)	-.016	X1(-4)	-.014	X1(-4)	-.015	X1(-4)	-.015	X1(-4)	-.015	X1(-4)	-.015
X3(-1)	-.010	X3(-1)	-.009	X2(-3)	.004	X2(-3)	.006	X2(-3)	.006	X2(-3)	.006	X2(-3)	.006	X2(-3)	.006	X2(-5)	-.002	X2(-1)	.006	X2(-1)	.006	X2(-1)	.007	X2(-1)	.008
X3(-2)	.015	X3(-2)	.013	X2(-6)	-.004	X2(-5)	-.006	X2(-5)	-.006	X2(-5)	-.007	X2(-5)	-.007	X2(-5)	-.007	X3(-2)	.004	X2(-5)	-.006	X2(-5)	-.007	X2(-5)	-.008	X2(-5)	-.008
X3(-6)	-.006	X3(-6)	-.006	X3(-1)	-.007	X3(-1)	-.007	X3(-1)	-.006	X3(-1)	-.008	X3(-1)	-.008	X3(-1)	-.007	X3(-6)	-.007	X3(-1)	.006	X3(-1)	.005	X3(-1)	.006	X3(-1)	.007
X4(-1)	-.028	X4(-1)	-.010	X3(-2)	.012	X3(-2)	.012	X3(-2)	.011	X3(-2)	.012	X3(-2)	.013	X3(-2)	.012	X4(-3)	.002	X3(-6)	-.007	X3(-6)	-.006	X3(-5)	-.008	X3(-5)	-.008
X4(-3)	.030	X4(-6)	.012	X3(-6)	-.006	X3(-6)	-.006	X3(-6)	-.006	X3(-6)	-.007	X3(-6)	-.007	X3(-6)	-.007	X5(-5)	-.016	X5(-5)	-.020	X5(-5)	-.020	X4(-5)	.002	X5(-5)	-.019
X5(-2)	-.011	X5(-2)	-.010	X4(-1)	-.026	X4(-1)	-.023	X4(-1)	-.023	X4(-1)	-.023	X4(-1)	-.025	X4(-1)	-.025	X5(-6)	.017	X5(-6)	.019	X5(-6)	.019	X5(-5)	-.019	X5(-6)	.018
X5(-6)	.011	X5(-6)	.010	X4(-3)	.027	X4(-3)	.025	X4(-3)	.025	X4(-3)	.025	X4(-3)	.026	X4(-3)	.026	X6(-1)	.006	X6(-1)	.021	X6(-1)	.018	X5(-6)	.018	X6(-1)	.020
X7(-1)	-.014	X6(-3)	.003	X5(-2)	-.009	X5(-4)	-.014	X5(-4)	-.013	X5(-4)	-.012	X5(-2)	-.009	X5(-5)	-.021	X6(-5)	-.004	X6(-2)	-.019	X6(-2)	-.013	X6(-1)	.021	X6(-2)	-.014
X7(-4)	.014	X7(-1)	-.012	X5(-6)	.009	X5(-6)	.014	X5(-6)	.014	X5(-6)	.013	X5(-6)	.009	X5(-6)	.022	X9(-5)	.012	X7(-4)	.014	X6(-5)	-.004	X6(-2)	-.019	X6(-5)	-.004
X8(-1)	-.044	X7(-4)	.011	X6(-4)	.011	X6(-4)	.012	X6(-4)	.013	X6(-4)	.013	X6(-1)	.006	X6(-4)	.014	X9(-6)	-.014	X7(-5)	-.014	X7(-4)	.014	X7(-1)	.006	X7(-1)	.006
X8(-2)	.043	X8(-1)	-.016	X6(-5)	-.009	X6(-5)	-.011	X6(-5)	-.012	X6(-5)	-.013	X6(-5)	-.005	X6(-5)	-.014	X10(-1)	.004	X9(-1)	-.019	X7(-5)	-.014	X7(-5)	-.007	X7(-5)	-.007
X9(-5)	.020	X8(-5)	.015	X10(-1)	.006	X9(-1)	-.013	X9(-5)	.014	X10(-1)	.005	X9(-5)	.012	X9(-5)	.011	X10(-6)	-.006	X9(-2)	.027	X9(-1)	-.019	X9(-1)	-.017	X9(-1)	-.014
X9(-6)	-.023	X9(-5)	.018	X10(-6)	-.006	X9(-2)	.020	X9(-6)	-.016	X10(-6)	-.006	X9(-6)	-.013	X9(-6)	-.012	X11(-2)	.007	X9(-6)	-.008	X9(-2)	.026	X9(-2)	.024	X9(-2)	.020
X10(-1)	.006	X9(-6)	-.020	X11(-2)	.008	X9(-6)	-.008	X10(-1)	.006	X11(-2)	.008	X10(-1)	.005	X10(-1)	.005	X11(-5)	-.006	X10(-1)	.005	X9(-6)	-.008	X9(-6)	-.007	X9(-6)	-.007
X10(-6)	-.006	X10(-1)	.006	X11(-6)	-.006	X10(-1)	.006	X10(-6)	-.006	X11(-5)	-.006	X10(-6)	-.006	X10(-6)	-.006	X13(-1)	.022	X10(-6)	-.005	X10(-1)	.005	X10(-1)	.004	X10(-1)	.005
X11(-3)	.010	X10(-6)	-.006	**X12(-3)**	**.003**	X10(-6)	-.006	X11(-2)	.009	X12(-1)	-.011	X11(-2)	.007	X11(-2)	.007	X13(-4)	-.026	X11(-1)	-.013	X10(-6)	-.005	X10(-6)	-.005	X10(-6)	-.005
X11(-6)	-.009	X11(-3)	.010	X13(-1)	.014	X11(-2)	.009	X11(-5)	-.007	X12(-2)	.014	X11(-5)	-.006	X11(-5)	-.006	X14(-2)	.002	X11(-2)	.020	X11(-1)	-.012	X11(-1)	-.010	X11(-3)	.010
X12(-5)	.003	X11(-6)	-.008	X13(-5)	-.042	X11(-5)	-.007	**X12(-4)**	**.003**	X13(-1)	.027	**X12(-5)**	**.003**	X12(-1)	-.013	X14(-6)	-.002	X11(-5)	-.007	X11(-2)	.020	X11(-2)	.019	X11(-5)	-.008
X13(-1)	.015	X12(-5)	.003	X13(-6)	.026	**X12(-4)**	**.003**	X13(-1)	.017	X13(-4)	-.053	X13(-1)	.030	X12(-2)	.015	X15(-1)	.003	X12(-1)	-.013	X11(-5)	-.008	X11(-5)	-.007	X13(-1)	.032
X13(-5)	-.018	X13(-1)	.015	**X14(-6)**	**-.003**	X13(-1)	.014	X13(-5)	-.056	X13(-6)	.023	X13(-4)	-.061	X13(-1)	.030	X15(-6)	-.002	X12(-2)	.018	X12(-1)	-.014	X12(-1)	-.010	X13(-4)	-.083
X14(-6)	**-.003**	X13(-5)	-.017	X15(-2)	.003	X13(-5)	-.044	X13(-6)	.037	X14(-1)	-.003	X13(-6)	.028	X13(-4)	-.062	X16(-2)	.002	X12(-6)	-.004	X12(-2)	.020	X12(-2)	.011	X13(-6)	.049
X15(-6)	-.003	**X14(-6)**	**-.003**	X15(-6)	-.004	X13(-6)	.028	**X14(-6)**	**-.002**	X14(-2)	.004	**X14(-6)**	**-.002**	X13(-6)	.030	X18(-3)	.004	X13(-1)	.029	X12(-6)	-.005	X13(-1)	.031	X18(-1)	-.011
X16(-2)	.024	X15(-2)	.003	X19(-5)	.004	**X14(-6)**	**-.002**	X15(-1)	.003	X14(-6)	-.003	X15(-6)	-.002	**X14(-6)**	**-.002**	X18(-4)	-.004	X13(-4)	-.066	X13(-1)	.029	X13(-4)	-.076	X18(-2)	.008
X16(-3)	-.022	X15(-6)	-.004	X19(-6)	-.005	X15(-1)	.003	X15(-6)	-.003	X15(-6)	-.002	X16(-2)	.009	X15(-1)	.002	X21(-6)	.003	X13(-6)	.035	X13(-4)	-.069	X13(-6)	.042	X19(-1)	-.008
X19(-3)	-.005	X16(-2)	.017	X21(-1)	.009	X15(-6)	-.003	X16(-2)	.002	X16(-2)	.002	X16(-4)	-.007	X15(-6)	-.003	X22(-1)	.015	X16(-2)	.003	X13(-6)	.038	X18(-1)	-.011	X19(-2)	.005

X19(-5)	.004	X16(-3)	-.016	X21(-2)	-.013	X16(-2)	.002	X19(-5)	.005	X19(-5)	.004	X19(-5)	.004	X16(-2)	.009	X22(-2)	-.020	X18(-1)	-.011	X16(-2)	.002	X18(-2)	.009	X20(-1)	-.020
X21(-1)	.008	X21(-1)	.009	X21(-6)	.004	X19(-5)	.005	X19(-6)	-.006	X19(-6)	-.006	X19(-6)	-.005	X16(-4)	-.007	X22(-6)	.005	X18(-2)	.009	X18(-1)	-.011	X19(-1)	-.008	X20(-2)	.021
X21(-2)	-.012	X21(-2)	-.011	X22(-1)	.016	X19(-6)	-.006	X20(-1)	-.003	X20(-1)	-.003	X20(-1)	-.006	X19(-2)	-.002	X23(-1)	-.012	X19(-1)	-.008	X18(-2)	.009	X19(-2)	.005	X21(-1)	.012
X22(-1)	.014	X22(-1)	.012	X22(-2)	-.023	X20(-1)	-.006	X20(-5)	.003	X20(-5)	.003	X20(-3)	.005	X19(-5)	.005	X23(-2)	.012	X19(-2)	.005	X19(-1)	-.008	X20(-1)	-.014	X21(-2)	-.012
X22(-2)	-.022	X22(-2)	-.019	X22(-6)	.008	X20(-3)	.006	X21(-1)	.008	X21(-1)	.009	X21(-1)	.009	X19(-6)	-.005	X24(-3)	-.005	X20(-1)	-.011	X19(-2)	.005	X20(-3)	.024	X22(-2)	-.002
X22(-6)	.010	X22(-6)	.008	X23(-1)	-.010	X21(-1)	.009	X21(-2)	-.009	X21(-2)	-.011	X21(-2)	-.013	X20(-1)	-.005	X24(-6)	.005	X20(-3)	.019	X20(-1)	-.012	X20(-6)	-.008	X23(-1)	-.012
X23(-1)	-.013	X23(-1)	-.010	X23(-3)	.011	X21(-2)	-.013	X22(-1)	.018	X21(-6)	.003	X21(-4)	.005	X20(-3)	.005	X26(-6)	-.003	X20(-6)	-.010	X20(-3)	.020	X21(-1)	.013	X23(-3)	.011
X23(-3)	.014	X23(-3)	.012	X24(-2)	-.009	X21(-6)	.003	X22(-2)	-.026	X22(-1)	.017	X22(-1)	.017	X21(-1)	.008	X27(-4)	-.004	X21(-1)	.016	X20(-6)	-.008	X21(-2)	-.013	X24(-1)	-.006
X24(-2)	-.010	X24(-2)	-.010	X24(-5)	.007	X22(-1)	.016	X22(-6)	.009	X22(-2)	-.025	X22(-2)	-.024	X21(-2)	-.011	X28(-6)	.002	X21(-2)	-.016	X21(-1)	.013	X22(-3)	-.003	X24(-6)	.004
X24(-5)	.008	X24(-5)	.008	X25(-4)	-.003	X22(-2)	-.024	X23(-1)	-.011	X22(-6)	.008	X22(-6)	.007	X21(-6)	.004	X29(-4)	-.011	X22(-2)	-.003	X21(-2)	-.013	X23(-1)	-.012	X26(-6)	-.002
X27(-4)	-.004	X25(-4)	-.003	X27(-4)	-.003	X22(-6)	.008	X23(-3)	.011	X23(-1)	-.011	X23(-1)	-.011	X22(-1)	.015	X29(-6)	.009	X23(-1)	-.013	X22(-2)	-.006	X23(-3)	.011	X27(-4)	-.003
X28(-6)	.004	X27(-4)	-.003	X29(-1)	.020	X23(-1)	-.010	X24(-2)	-.009	X23(-3)	.011	X23(-3)	.011	X22(-2)	-.022	X30(-6)	-.002	X23(-3)	.012	X22(-6)	.004	X24(-2)	-.008	X29(-4)	-.018
X30(-2)	.005	X30(-6)	-.003	X29(-2)	-.027	X23(-3)	.011	X24(-5)	.007	X24(-2)	-.007	X24(-2)	-.007	X22(-6)	.006	X31(-3)	.030	X24(-2)	-.005	X23(-1)	-.012	X24(-5)	.006	X29(-6)	.016
X30(-6)	-.007	X31(-1)	-.024	X29(-6)	.007	X24(-2)	-.009	X25(-3)	-.002	X24(-5)	.006	X24(-5)	.005	X23(-1)	-.005	X31(-5)	-.028	X24(-6)	.004	X23(-3)	.011	X25(-1)	-.002	X31(-1)	-.024
X31(-1)	-.029	X31(-3)	.056	X30(-6)	-.003	X24(-5)	.007	X26(-6)	-.002	X25(-1)	.009	X25(-1)	.010	X23(-6)	.004	X32(-5)	.003	X27(-4)	-.003	X24(-2)	-.007	X26(-6)	-.003	X31(-3)	.042
X31(-3)	.064	X31(-5)	-.029	X31(-1)	-.023	X25(-5)	-.002	X27(-4)	-.003	X25(-3)	-.011	X25(-3)	-.012	X24(-2)	-.007	X34(-4)	-.002	X29(-4)	-.015	X24(-5)	.006	X27(-4)	-.003	X31(-5)	-.018
X31(-5)	-.032	X33(-1)	.003	X31(-3)	.055	X27(-4)	-.003	X29(-4)	-.012	X26(-6)	-.002	X26(-6)	-.003	X24(-5)	.005	X35(-6)	-.002	X29(-6)	.012	X26(-6)	-.002	X28(-6)	.002	X32(-1)	-.022
X32(-1)	.022	X35(-6)	-.003	X31(-5)	-.030	X29(-4)	-.012	X29(-6)	.011	X27(-4)	-.003	X27(-4)	-.004	X25(-1)	.018			X31(-1)	-.024	X27(-4)	-.003	X29(-4)	-.017	X32(-2)	.024
X32(-2)	-.019			X35(-6)	-.003	X29(-6)	.011	X30(-5)	.019	X29(-4)	-.012	X29(-4)	-.013	X25(-2)	-.020			X31(-3)	.046	X29(-4)	-.016	X29(-6)	.014	X33(-5)	.020
X34(-1)	-.009					X30(-5)	.017	X30(-6)	-.021	X29(-6)	.010	X29(-6)	.010	X26(-6)	-.002			X31(-5)	-.021	X29(-6)	.014	X30(-2)	-.002	X33(-6)	-.019
X34(-6)	.008					X30(-6)	-.020	X31(-1)	-.024	X30(-2)	.007	X30(-2)	.008	X27(-4)	-.003			**X32(-5)**	**.002**	X31(-1)	-.024	X31(-3)	.023	X35(-1)	.006
X35(-4)	.006					X31(-1)	-.024	X31(-3)	.053	X30(-6)	-.009	X30(-6)	-.010	X29(-4)	-.012					X31(-3)	.044	X31(-5)	-.021	X35(-3)	-.006
X35(-6)	-.009					X31(-3)	.054	X31(-5)	-.028	X31(-1)	-.026	X31(-1)	-.027	X29(-6)	.010					X31(-5)	-.020	X32(-1)	-.008		
						X31(-5)	-.028	X35(-2)	.004	X31(-3)	.053	X31(-3)	.052	X30(-2)	.007					**X32(-5)**	**.002**	X32(-5)	.010		
						X32(-4)	-.015	X35(-6)	-.006	X31(-5)	-.026	X31(-5)	-.025	X30(-6)	-.009					X33(-5)	.023	X33(-5)	.023		
						X32(-5)	.018			X32(-4)	-.015	X32(-5)	.003	X31(-1)	-.024					X33(-6)	-.022	X33(-6)	-.022		
						X35(-2)	.005			X32(-5)	.017	X34(-4)	-.002	X31(-3)	.047					X35(-1)	.004	X34(-1)	.007		
						X35(-6)	-.006			X35(-6)	-.006	X35(-6)	-.006	X31(-5)	-.023					X35(-4)	-.004	X34(-4)	-.009		
														X32(-4)	-.016							X35(-1)	.005		
														X32(-5)	.018							X35(-3)	-.006		

Table 5.9 Korea: Weights of disaggregate indicators

00M6		01M6		02M6		03M6		04M6		05M6		06M6		07M6		08M6		09M6		10M6		11M6		12M6	
X1(-2)	0.009	X1(-3)	0.009	X1(-3)	0.010	X1(-3)	0.010	X1(-3)	0.011	X1(-3)	0.011	X1(-3)	0.011	X1(-3)	0.011	X1(-3)	0.009	X2(-1)	0.011	X2(-1)	0.012	X2(-1)	0.012	X2(-1)	0.014
X1(-6)	-0.008	X1(-6)	-0.008	X1(-6)	-0.008	X1(-6)	-0.008	X1(-6)	-0.011	X1(-6)	-0.011	X1(-6)	-0.011	X1(-6)	-0.011	X1(-6)	-0.010	X2(-5)	-0.012	X2(-5)	-0.013	X2(-5)	-0.014	X2(-5)	-0.015
X2(-1)	0.004	X2(-1)	0.006	X2(-1)	0.005	X2(-1)	0.006	X2(-1)	0.006	X2(-1)	0.006	X2(-1)	0.007	X2(-1)	0.007	X2(-1)	0.004	X3(-1)	0.012	X3(-1)	0.012	X3(-1)	0.011	X3(-1)	0.013
X3(-2)	0.006	X2(-4)	-0.004	X2(-6)	-0.005	X2(-5)	-0.007	X2(-5)	-0.008	X2(-5)	-0.009	X2(-5)	-0.010	X2(-5)	-0.010	X2(-5)	-0.008	X3(-5)	-0.013	X3(-5)	-0.013	X3(-5)	-0.014	X3(-5)	-0.014
X3(-5)	0.009	X3(-2)	0.006	X3(-2)	0.008	X3(-2)	0.007	X3(-2)	0.007	X3(-2)	0.006	X3(-2)	0.006	X3(-2)	0.007	X3(-3)	0.005	X5(-5)	-0.023	X5(-5)	-0.022	X4(-3)	0.002	X5(-5)	-0.021
X3(-6)	-0.014	X3(-5)	0.007	X3(-6)	-0.007	X3(-6)	-0.007	X3(-6)	-0.008	X3(-6)	-0.009	X3(-6)	-0.009	X3(-6)	-0.010	X3(-6)	-0.010	X5(-6)	0.021	X5(-6)	0.020	X5(-5)	-0.022	X5(-6)	0.019
X4(-1)	-0.029	X3(-6)	-0.012	X4(-1)	-0.038	X4(-1)	-0.015	X4(-1)	-0.014	X4(-1)	-0.015	X4(-1)	-0.015	X4(-1)	-0.015	X5(-5)	-0.016	X6(-1)	0.026	X6(-1)	0.025	X5(-6)	0.019	X6(-1)	0.027
X4(-6)	0.028	X4(-1)	-0.022	X4(-3)	0.038	X4(-6)	0.016	X4(-6)	0.015	X4(-6)	0.017	X4(-6)	0.017	X4(-6)	0.017	X5(-6)	0.016	X6(-2)	-0.018	X6(-2)	-0.018	X6(-1)	0.011	X6(-2)	-0.018
X5(-1)	-0.007	X4(-6)	0.022	X5(-4)	-0.016	X5(-4)	-0.017	X5(-4)	-0.015	X5(-4)	-0.014	X5(-4)	-0.014	X5(-5)	-0.023	X6(-1)	0.006	X6(-6)	-0.007	X6(-6)	-0.007	X6(-6)	-0.011	X6(-5)	-0.008
X5(-5)	-0.015	X5(-4)	-0.016	X5(-6)	0.016	X5(-6)	0.017	X5(-6)	0.015	X5(-6)	0.015	X5(-6)	0.015	X5(-6)	0.024	X6(-6)	-0.006	X7(-1)	0.015	X7(-1)	0.015	X7(-1)	0.015	X7(-1)	0.015
X5(-6)	0.020	X5(-6)	0.015	X6(-1)	0.007	X6(-1)	0.006	X6(-1)	0.006	X6(-1)	0.007	X6(-1)	0.006	X6(-1)	0.007	X8(-6)	0.002	X7(-5)	-0.014	X7(-5)	-0.015	X7(-5)	-0.015	X7(-5)	-0.015
X6(-1)	0.005	X6(-1)	0.006	X6(-5)	-0.005	X6(-5)	-0.006	X6(-6)	-0.007	X6(-5)	-0.008	X6(-6)	-0.007	X6(-6)	-0.008	X9(-5)	0.015	X9(-1)	-0.016	X9(-1)	-0.015	X9(-1)	-0.013	X9(-1)	-0.011
X6(-6)	-0.003	X6(-5)	-0.003	X8(-2)	0.012	X9(-5)	0.020	X7(-2)	0.009	X7(-2)	0.010	X7(-2)	0.010	X7(-2)	0.010	X9(-6)	-0.016	X9(-3)	0.030	X9(-3)	0.029	X9(-3)	0.027	X9(-3)	0.023
X7(-1)	-0.020	X7(-1)	-0.017	X8(-6)	-0.013	X9(-6)	-0.020	X7(-5)	-0.010	X7(-5)	-0.010	X7(-5)	-0.010	X7(-5)	-0.010	X10(-6)	-0.003	X9(-6)	-0.013	X9(-6)	-0.013	X9(-6)	-0.011	X9(-6)	-0.011
X7(-2)	0.021	X7(-2)	0.016	X9(-5)	0.021	X10(-1)	0.005	X8(-1)	0.012	X8(-1)	0.011	X8(-1)	0.011	X9(-5)	0.014	X11(-3)	0.008	X10(-1)	0.005	X11(-3)	0.003	X11(-3)	0.004	X10(-1)	0.004
X9(-2)	0.011	X9(-5)	0.023	X9(-6)	-0.021	X10(-6)	-0.005	X8(-5)	-0.012	X8(-5)	-0.010	X8(-5)	-0.009	X9(-6)	-0.014	X11(-5)	-0.007	X10(-5)	-0.005	X13(-1)	0.022	X12(-2)	0.003	X10(-5)	-0.005
X9(-6)	-0.012	X9(-6)	-0.024	X10(-1)	0.006	X11(-3)	0.011	X9(-5)	0.018	X9(-5)	0.016	X9(-5)	0.015	X10(-1)	0.004	X12(-3)	0.003	X11(-1)	-0.011	X13(-4)	-0.063	X13(-1)	0.024	X11(-3)	0.003
X10(-1)	0.005	X10(-1)	0.006	X10(-6)	-0.004	X11(-5)	-0.009	X9(-6)	-0.017	X9(-6)	-0.015	X9(-6)	-0.014	X10(-6)	-0.005	X13(-1)	0.014	X11(-2)	0.013	X13(-6)	0.037	X13(-4)	-0.071	X12(-2)	0.003
X10(-6)	-0.005	X10(-6)	-0.005	X11(-3)	0.009	**X12(-4)**	**0.004**	X10(-1)	0.006	X10(-1)	0.005	X10(-1)	0.005	X11(-3)	0.009	X13(-5)	-0.019	X13(-1)	0.025	X18(-1)	-0.017	X13(-6)	0.043	X13(-1)	0.025
X11(-3)	0.010	X11(-3)	0.009	X11(-6)	-0.007	X13(-1)	0.010	X10(-6)	-0.006	X10(-6)	-0.005	X10(-6)	-0.005	X11(-5)	-0.007	X15(-1)	0.004	X13(-4)	-0.061	X18(-2)	0.012	X18(-1)	-0.017	X13(-4)	-0.078
X11(-6)	-0.008	X11(-6)	-0.007	X12(-4)	0.004	X13(-5)	-0.013	X11(-3)	0.011	X11(-3)	0.010	X11(-3)	0.009	X12(-1)	-0.013	X16(-5)	0.002	X13(-6)	0.032	X19(-1)	-0.009	X18(-2)	0.012	X13(-6)	0.050
X12(-5)	0.015	X12(-5)	0.017	X13(-1)	0.011	X15(-1)	0.004	X11(-5)	-0.008	X11(-5)	-0.007	X11(-5)	-0.007	**X12(-2)**	**0.016**	X19(-1)	0.002	X15(-5)	-0.003	X19(-3)	0.004	X19(-1)	-0.009	X18(-1)	-0.017
X12(-6)	-0.013	X12(-6)	-0.014	X13(-5)	-0.013	X15(-6)	-0.003	**X12(-2)**	**0.005**	**X12(-3)**	**0.005**	**X12(-1)**	**-0.006**	X13(-5)	-0.005	X21(-6)	0.005	X16(-5)	0.003	X20(-1)	-0.011	X19(-3)	0.004	X18(-2)	0.011
X13(-1)	0.013	X13(-3)	0.020	X15(-1)	0.004	X19(-4)	0.003	X13(-1)	0.012	X13(-1)	0.012	X12(-3)	0.010	X15(-1)	0.003	X24(-3)	-0.006	X18(-1)	-0.017	X20(-4)	0.025	X20(-1)	-0.018	X19(-1)	-0.009
X13(-5)	-0.014	X13(-5)	-0.023	X15(-6)	-0.003	X19(-6)	-0.005	X13(-5)	-0.017	X13(-5)	-0.017	X13(-1)	0.011	X15(-5)	-0.003	X24(-5)	0.006	X18(-2)	0.012	X20(-6)	-0.013	X20(-3)	0.022	X19(-3)	0.004
X15(-1)	0.004	X15(-1)	0.004	X19(-4)	0.003	X20(-1)	-0.004	X15(-1)	0.004	X15(-1)	0.004	X13(-5)	-0.016	X16(-4)	0.002	X25(-5)	-0.002	X19(-1)	-0.008	X21(-1)	0.011	X21(-1)	0.014	X20(-1)	-0.018

X15(-6)	-0.003	X15(-6)	-0.003	X19(-6)	-0.005	X20(-5)	0.004	X15(-5)	-0.003	X15(-5)	-0.003	X15(-1)	0.003	X18(-1)	-0.003	X26(-6)	-0.005	X19(-3)	0.004	X21(-4)	-0.009	X21(-3)	-0.012	X20(-3)	0.019
X16(-3)	-0.011	X16(-3)	-0.016	X20(-1)	-0.004	X22(-2)	-0.008	X19(-6)	-0.004	X18(-1)	-0.003	X15(-5)	-0.003	X19(-6)	-0.004	X27(-6)	-0.005	X20(-1)	-0.011	**X22(-2)**	**-0.005**	**X22(-2)**	**-0.006**	X21(-1)	0.010
X16(-5)	0.011	X16(-5)	0.016	X20(-5)	0.004	X22(-6)	0.005	X20(-1)	-0.004	X19(-6)	-0.004	X16(-4)	0.002	X20(-2)	-0.005	X28(-5)	0.004	X20(-4)	0.026	**X23(-1)**	**-0.003**	**X23(-1)**	**-0.003**	X21(-4)	-0.009
X20(-1)	-0.004	X19(-6)	-0.002	X22(-2)	-0.005	X23(-1)	-0.007	X20(-5)	0.005	X20(-1)	-0.004	X18(-1)	-0.003	X20(-5)	0.005	X29(-4)	-0.004	X20(-6)	-0.017	**X24(-1)**	**-0.004**	**X24(-1)**	**-0.005**	**X22(-2)**	**-0.005**
X20(-5)	0.010	X22(-2)	-0.006	X22(-5)	-0.013	X23(-6)	0.006	X22(-2)	-0.009	X20(-5)	0.005	X19(-6)	-0.004	X21(-2)	0.002	X30(-6)	-0.004	X21(-1)	0.021	**X25(-1)**	**-0.003**	**X25(-1)**	**-0.004**	**X23(-1)**	**-0.003**
X20(-6)	-0.008	X22(-5)	-0.013	X22(-6)	0.016	X24(-3)	-0.012	X22(-6)	0.006	X21(-1)	0.009	X20(-2)	-0.005	X22(-2)	-0.004	X32(-5)	0.005	X21(-2)	-0.019	**X26(-6)**	**-0.003**	**X26(-6)**	**-0.004**	**X24(-1)**	**-0.004**
X21(-4)	-0.005	X22(-6)	0.018	X23(-1)	-0.007	X24(-5)	0.009	X23(-1)	-0.008	X21(-2)	-0.006	X20(-5)	0.006	X23(-1)	-0.003	X34(-6)	-0.004	**X22(-2)**	**-0.006**	**X27(-6)**	**-0.004**	**X27(-6)**	**-0.004**	**X25(-1)**	**-0.003**
X21(-6)	0.003	X23(-1)	-0.008	X23(-6)	0.006	X25(-1)	0.010	X23(-6)	0.006	X22(-2)	-0.009	X21(-1)	0.003	X24(-3)	-0.009	X35(-6)	-0.002	**X23(-1)**	**-0.003**	**X29(-4)**	**-0.017**	**X28(-5)**	**0.003**	**X26(-6)**	**-0.003**
X22(-2)	-0.006	X23(-6)	0.007	X24(-3)	-0.009	X25(-3)	-0.013	X24(-3)	-0.012	X22(-6)	0.004	X22(-2)	-0.005	X24(-5)	0.007			**X24(-2)**	**-0.004**	**X29(-6)**	**0.013**	**X29(-4)**	**-0.017**	**X27(-6)**	**-0.003**
X22(-5)	-0.016	X24(-3)	-0.010	X24(-6)	0.007	X27(-4)	-0.002	X24(-5)	0.009	X23(-1)	-0.008	X23(-1)	-0.008	X25(-1)	0.026			**X25(-1)**	**-0.003**	**X30(-4)**	**-0.003**	**X29(-6)**	**0.012**	**X28(-5)**	**0.002**
X22(-6)	0.022	X24(-6)	0.008	X25(-1)	0.011	X29(-4)	-0.012	X25(-1)	0.023	X23(-6)	0.006	X23(-6)	0.005	X25(-2)	-0.029			**X26(-6)**	**-0.003**	**X32(-1)**	**-0.027**	**X30(-4)**	**-0.004**	**X29(-4)**	**-0.020**
X23(-1)	-0.008	X25(-6)	-0.003	X25(-3)	-0.014	X29(-6)	0.010	X25(-2)	-0.027	X24(-3)	-0.010	X24(-3)	-0.009	X26(-6)	-0.004			**X27(-6)**	**-0.003**	**X32(-3)**	**0.030**	**X32(-1)**	**-0.028**	**X29(-6)**	**0.015**
X23(-6)	0.006	X27(-6)	-0.002	X27(-4)	-0.002	X30(-1)	0.008	X26(-6)	-0.003	X24(-5)	0.007	X24(-5)	0.006	X27(-6)	-0.004			**X29(-5)**	**-0.028**	X33(-4)	0.018	**X32(-3)**	**0.032**	**X30(-4)**	**-0.003**
X24(-3)	-0.010	X29(-5)	-0.018	X29(-4)	-0.011	X30(-6)	-0.011	X27(-6)	-0.003	X25(-1)	0.013	X25(-1)	0.025	X28(-2)	0.002			**X29(-6)**	**0.024**	X33(-6)	-0.017	X34(-2)	0.021	**X32(-1)**	**-0.029**
X24(-6)	0.009	X29(-6)	0.016	X29(-6)	0.008	X35(-2)	0.008	X29(-1)	0.010	X25(-3)	-0.018	X25(-2)	-0.029	X29(-5)	-0.020			**X32(-1)**	**-0.027**	X34(-2)	0.021	X34(-3)	-0.024	**X32(-3)**	**0.032**
X25(-1)	0.014	X30(-4)	0.009	X30(-1)	0.007	X35(-6)	-0.009	X29(-3)	-0.021	X26(-6)	-0.004	X26(-6)	-0.004	X29(-6)	0.016			**X32(-3)**	**0.030**	X34(-3)	-0.024	X35(-2)	0.008	X33(-1)	-0.025
X25(-2)	-0.016	X30(-6)	-0.012	X30(-6)	-0.010			X29(-6)	0.008	X27(-6)	-0.004	X27(-6)	-0.004	X30(-1)	0.009			X34(-1)	0.011	X35(-2)	0.008	X35(-4)	-0.008	X33(-2)	0.025
X27(-6)	-0.003	X35(-2)	0.006	X35(-2)	0.007			X30(-1)	0.010	X28(-2)	0.002	X28(-5)	0.002	X30(-6)	-0.013			X34(-4)	-0.013	X35(-4)	-0.007			X34(-2)	0.013
X28(-1)	0.004	X35(-6)	-0.008	X35(-6)	-0.010			X30(-6)	-0.014	X29(-3)	-0.004	X29(-3)	-0.004	X32(-2)	-0.008			X35(-2)	0.008					X34(-4)	-0.016
X29(-5)	-0.020							X32(-2)	-0.007	X30(-1)	0.010	X30(-1)	0.010	X32(-5)	0.012			X35(-4)	-0.007					X35(-2)	0.008
X29(-6)	0.016							X32(-5)	0.010	X30(-6)	-0.014	X30(-6)	-0.014	X34(-3)	-0.003									X35(-4)	-0.008
X30(-1)	0.007							X35(-2)	0.008	X32(-2)	-0.008	X32(-5)	0.004	X35(-2)	0.005										
X30(-6)	-0.008							X35(-6)	-0.009	X32(-5)	0.012	X34(-3)	-0.003	X35(-6)	-0.005										
X32(-1)	0.012									X34(-3)	-0.003	X35(-2)	0.005												
X32(-2)	-0.012									X35(-2)	0.005	X35(-6)	-0.005												
X34(-1)	-0.006									X35(-6)	-0.005														
X34(-6)	0.006																								
X35(-2)	0.008																								
X35(-6)	-0.009																								

Table 5.10 Taiwan: Weights of disaggregate indicators

00M6		01M6		02M6		03M6		04M6		05M6		06M6		07M6		08M6		09M6		10M6		11M6		12M6	
X1(-2)	0.009	X1(-2)	0.010	X1(-2)	0.010	X1(-2)	0.010	X1(-2)	0.010	X1(-2)	0.009	X1(-2)	0.010	X1(-1)	0.009	X1(-2)	0.008	X1(-1)	0.009	X1(-1)	0.009	X1(-1)	0.008	X1(-1)	0.008
X1(-5)	-0.006	X1(-5)	-0.007	X1(-5)	-0.007	X1(-5)	-0.007	X1(-5)	-0.008	X1(-5)	-0.008	X1(-5)	-0.009	X1(-5)	-0.008	X1(-5)	-0.008	X1(-5)	-0.008	X1(-5)	-0.008	X1(-5)	-0.008	X1(-5)	-0.008
X2(-3)	0.004	X2(-3)	0.004	X2(-3)	0.004	X2(-3)	0.004	X2(-3)	0.005	X2(-3)	0.005	X2(-3)	0.005	X2(-3)	0.005	X2(-6)	-0.004	X2(-1)	0.006	X2(-1)	0.007	X2(-1)	0.008	X2(-1)	0.008
X2(-6)	-0.003	X2(-6)	-0.003	X2(-6)	-0.005	X2(-6)	-0.006	X2(-6)	-0.007	X2(-6)	-0.007	X2(-6)	-0.008	X2(-6)	-0.008	X3(-3)	0.005	X2(-6)	-0.008	X2(-6)	-0.008	X2(-5)	-0.010	X2(-6)	-0.010
X3(-3)	0.007	X3(-3)	0.007	X3(-3)	0.007	X3(-3)	0.007	X3(-3)	0.006	X3(-3)	0.007	X3(-3)	0.007	X3(-3)	0.007	X3(-6)	-0.010	X3(-1)	0.009	X3(-1)	0.009	X3(-1)	0.009	X3(-1)	0.010
X3(-6)	-0.007	X3(-6)	-0.007	X3(-6)	-0.008	X3(-6)	-0.008	X3(-6)	-0.008	X3(-6)	-0.009	X3(-6)	-0.010	X3(-6)	-0.010	X4(-6)	0.002	X3(-5)	-0.011	X3(-5)	-0.011	X3(-5)	-0.011	X3(-5)	-0.012
X4(-1)	-0.026	X4(-1)	-0.020	X4(-1)	-0.017	X4(-1)	-0.015	X4(-1)	-0.013	X4(-1)	-0.013	X4(-1)	-0.011	X4(-1)	-0.011	X6(-1)	0.005	X6(-1)	0.008	X6(-1)	0.008	X4(-3)	0.003	X4(-3)	0.002
X4(-6)	0.026	X4(-6)	0.021	X4(-5)	0.018	X4(-5)	0.017	X4(-5)	0.015	X4(-5)	0.015	X4(-6)	0.013	X4(-6)	0.013	X6(-6)	-0.004	X6(-6)	-0.008	X6(-6)	-0.008	X5(-3)	-0.002	X5(-3)	-0.002
X5(-4)	-0.012	X5(-2)	-0.009	X5(-2)	-0.008	X5(-4)	-0.012	X5(-4)	-0.010	X5(-4)	-0.009	X5(-4)	-0.010	X5(-4)	-0.010	X9(-5)	0.013	X7(-1)	0.007	X7(-1)	0.007	X6(-1)	0.009	X6(-1)	0.008
X5(-6)	0.012	X5(-6)	0.009	X5(-6)	0.008	X5(-6)	0.012	X5(-6)	0.010	X5(-6)	0.010	X5(-6)	0.011	X5(-6)	0.010	X9(-6)	-0.014	X7(-6)	-0.007	X7(-6)	-0.008	X6(-6)	-0.008	X6(-6)	-0.008
X7(-1)	-0.026	X6(-2)	0.003	X6(-1)	0.002	X6(-4)	0.006	X6(-4)	0.005	X6(-1)	0.004	X6(-1)	0.004	X6(-1)	0.005	X10(-6)	-0.003	X9(-1)	-0.012	X9(-1)	-0.011	X7(-1)	0.008	X7(-1)	0.008
X7(-2)	0.018	X7(-1)	-0.011	X7(-1)	-0.015	X6(-6)	-0.005	X6(-6)	-0.006	X6(-6)	-0.005	X6(-6)	-0.005	X6(-6)	-0.005	X11(-3)	0.005	X9(-3)	0.023	X9(-3)	0.022	X7(-6)	-0.008	X7(-6)	-0.008
X7(-5)	0.009	X7(-5)	0.010	X7(-2)	0.014	X7(-1)	-0.015	X9(-5)	0.015	X9(-5)	0.014	X9(-5)	0.012	X9(-5)	0.012	X11(-6)	-0.004	X9(-6)	-0.011	X9(-6)	-0.011	X9(-1)	-0.009	X9(-1)	-0.008
X8(-1)	-0.012	X9(-5)	0.019	X9(-5)	0.017	X7(-2)	0.013	X9(-6)	-0.015	X9(-6)	-0.014	X9(-6)	-0.012	X9(-6)	-0.012	X12(-3)	0.007	X10(-1)	0.004	X11(-3)	0.003	X9(-3)	0.019	X9(-3)	0.017
X8(-4)	0.012	X9(-6)	-0.020	X9(-6)	-0.018	X9(-5)	0.016	X10(-1)	0.004	X10(-1)	0.004	X10(-1)	0.004	X10(-1)	0.003	X12(-6)	-0.005	X10(-5)	-0.004	X12(-3)	0.013	X9(-6)	-0.009	X9(-6)	-0.008
X9(-5)	0.018	X10(-1)	0.005	X10(-1)	0.005	X9(-6)	-0.017	X10(-6)	-0.004	X10(-6)	-0.004	X10(-6)	-0.004	X10(-6)	-0.004	X13(-1)	0.020	X11(-3)	0.002	X12(-4)	-0.011	X10(-5)	-0.002	X10(-1)	0.003
X9(-6)	-0.020	X10(-5)	-0.004	X10(-5)	-0.004	X10(-1)	0.004	X11(-3)	0.007	X11(-3)	0.006	X11(-3)	0.007	X11(-3)	0.007	X13(-4)	-0.024	X12(-3)	0.006	X13(-1)	0.024	X11(-3)	0.003	X10(-5)	-0.004
X10(-2)	0.004	X11(-2)	0.006	X11(-3)	0.008	X10(-5)	-0.004	X11(-6)	-0.004	X11(-6)	-0.004	X11(-5)	-0.005	X11(-5)	-0.005	X15(-1)	0.004	X12(-6)	-0.005	X13(-4)	-0.064	X12(-3)	0.013	X11(-3)	0.003
X10(-6)	-0.003	X11(-6)	-0.004	X11(-6)	-0.005	X11(-3)	0.007	X12(-1)	-0.005	X12(-1)	-0.005	X12(-1)	-0.006	X12(-1)	-0.007	X15(-6)	-0.002	X13(-1)	0.015	X13(-6)	0.036	X12(-4)	-0.010	X12(-3)	0.008
X11(-2)	0.006	**X12(-3)**	**0.004**	X12(-1)	-0.007	X11(-6)	-0.005	X12(-3)	0.010	X12(-3)	0.010	X12(-3)	0.010	X12(-3)	0.010	X16(-2)	0.002	X13(-5)	-0.069	X16(-4)	0.002	X13(-1)	0.026	X12(-5)	-0.006
X11(-6)	-0.004	X13(-1)	0.015	X12(-3)	0.011	X12(-1)	-0.005	X13(-1)	0.014	X13(-1)	0.022	X13(-1)	0.024	X13(-1)	0.025	X18(-1)	0.003	X13(-6)	0.051	X18(-1)	-0.008	X13(-4)	-0.071	X13(-1)	0.026
X12(-3)	0.004	X13(-5)	-0.018	X13(-1)	0.012	X12(-3)	0.009	X13(-5)	-0.044	X13(-4)	-0.044	X13(-4)	-0.051	X13(-4)	-0.056	X18(-4)	-0.004	X15(-4)	-0.002	X18(-3)	0.005	X13(-6)	0.041	X13(-4)	-0.077
X13(-1)	0.018	X14(-4)	-0.002	X13(-5)	-0.031	X13(-1)	0.012	X13(-6)	0.025	X13(-6)	0.018	X13(-6)	0.023	X13(-6)	0.027	X19(-1)	0.003	X16(-6)	0.003	X19(-1)	-0.006	X18(-1)	-0.008	X13(-6)	0.047
X13(-4)	-0.021	X15(-1)	0.004	X13(-6)	0.016	X13(-5)	-0.034	X14(-4)	-0.002	X14(-4)	-0.002	X15(-1)	0.004	X15(-1)	0.004	X19(-6)	-0.002	X18(-1)	-0.008	X19(-3)	0.003	X18(-3)	0.005	X18(-1)	-0.008
X15(-1)	0.004	X15(-6)	-0.003	X14(-4)	-0.002	X13(-6)	0.018	X15(-1)	0.004	X15(-1)	0.004	X15(-6)	-0.003	X15(-6)	-0.002	X21(-1)	0.004	X18(-3)	0.005	X20(-1)	-0.010	X19(-1)	-0.007	X18(-3)	0.004

X15(-6)	-0.003	X19(-6)	-0.003	X15(-1)	0.004	X14(-4)	-0.002	X15(-6)	-0.003	X15(-6)	-0.002	X16(-2)	0.003	X16(-2)	0.003	X22(-2)	-0.004	X19(-1)	-0.006	X20(-4)	0.026	X19(-3)	0.003	X19(-1)	-0.007
X20(-1)	-0.004	X20(-1)	-0.005	X15(-6)	-0.003	X15(-1)	0.004	X16(-4)	0.002	X16(-2)	0.003	X19(-6)	-0.004	X18(-5)	-0.002	X22(-6)	0.004	X19(-3)	0.003	X20(-5)	-0.014	X20(-1)	-0.026	X19(-3)	0.003
X20(-4)	0.004	X20(-4)	0.005	X19(-6)	-0.003	X15(-6)	-0.003	X19(-6)	-0.004	X19(-6)	-0.004	X20(-1)	-0.005	X19(-6)	-0.004	X24(-3)	-0.004	X20(-1)	-0.009	X21(-1)	0.016	X20(-2)	0.029	X20(-1)	-0.027
X21(-3)	-0.003	X22(-2)	-0.008	X20(-1)	-0.006	X19(-6)	-0.003	X20(-1)	-0.005	X20(-1)	-0.005	X20(-4)	0.006	X20(-1)	-0.005	X24(-6)	0.003	X20(-4)	0.020	X21(-2)	-0.010	X21(-1)	0.015	X20(-2)	0.028
X22(-2)	-0.008	X22(-6)	0.007	X20(-4)	0.006	X20(-1)	-0.005	X20(-4)	0.006	X20(-4)	0.006	X21(-1)	0.007	X20(-4)	0.005	X25(-4)	-0.002	X20(-6)	-0.012	X21(-5)	-0.004	X21(-2)	-0.010	X21(-1)	0.015
X22(-6)	0.008	X24(-2)	-0.007	X22(-1)	0.009	X20(-4)	0.006	X21(-1)	0.003	X21(-1)	0.004	X21(-2)	-0.006	X21(-1)	0.002	X26(-5)	-0.005	X21(-1)	0.019	**X22(-2)**	**-0.004**	X21(-5)	-0.004	X21(-2)	-0.008
X24(-2)	-0.007	X24(-6)	0.004	X22(-2)	-0.016	X21(-1)	0.005	X21(-4)	-0.003	X21(-4)	-0.003	X22(-2)	-0.008	X22(-2)	-0.007	X27(-5)	-0.005	X21(-2)	-0.017	**X24(-2)**	**-0.003**	**X22(-2)**	**-0.005**	X21(-4)	-0.006
X24(-6)	0.005	X25(-3)	-0.004	X22(-6)	0.007	X21(-2)	-0.006	X22(-1)	0.009	X22(-2)	-0.009	X22(-6)	0.005	X22(-6)	0.004	X28(-5)	0.003	**X22(-2)**	**-0.004**	**X25(-2)**	**-0.002**	**X24(-2)**	**-0.004**	**X22(-2)**	**-0.004**
X25(-5)	-0.003	**X26(-4)**	**-0.002**	X24(-3)	-0.008	X22(-1)	0.009	X22(-2)	-0.019	X22(-6)	0.006	X24(-3)	-0.003	X24(-3)	-0.007	X29(-4)	-0.003	**X24(-2)**	**-0.004**	**X26(-4)**	**-0.003**	**X25(-2)**	**-0.003**	**X24(-1)**	**-0.004**
X26(-5)	**-0.003**	**X27(-4)**	**-0.003**	X24(-6)	0.005	X22(-2)	-0.017	X22(-6)	0.007	X24(-3)	-0.007	X25(-1)	0.011	X24(-5)	0.005	X30(-6)	-0.004	**X25(-2)**	**-0.002**	**X27(-5)**	**-0.004**	**X26(-5)**	**-0.004**	**X25(-2)**	**-0.003**
X27(-5)	**-0.004**	X28(-1)	0.002	X25(-1)	0.010	X22(-6)	0.007	X24(-3)	-0.008	X24(-6)	0.004	X25(-3)	-0.015	X25(-1)	0.011	X31(-1)	0.012	**X26(-4)**	**-0.003**	**X28(-5)**	**0.002**	**X27(-5)**	**-0.004**	**X26(-4)**	**-0.003**
X28(-3)	0.004	X28(-6)	-0.004	X25(-3)	-0.014	X24(-2)	-0.006	X24(-6)	0.005	X25(-1)	0.011	**X26(-5)**	**-0.004**	X25(-3)	-0.014	X31(-6)	-0.010	**X27(-5)**	**-0.004**	**X29(-1)**	**0.008**	**X28(-5)**	**0.003**	**X27(-5)**	**-0.004**
X29(-4)	-0.002	X30(-2)	0.006	**X26(-5)**	**-0.002**	X24(-6)	0.003	X25(-1)	0.012	X25(-3)	-0.015	**X27(-5)**	**-0.004**	**X26(-5)**	**-0.004**	X32(-6)	0.005	**X29(-1)**	**0.007**	**X29(-4)**	**-0.024**	**X29(-1)**	**0.008**	**X28(-5)**	**0.002**
X30(-1)	0.006	X30(-6)	-0.009	**X27(-4)**	**-0.003**	X25(-1)	0.011	X25(-3)	-0.017	**X26(-5)**	**-0.004**	X28(-3)	0.002	**X27(-5)**	**-0.004**	X34(-6)	-0.004	**X29(-4)**	**-0.022**	**X29(-6)**	**0.013**	**X29(-4)**	**-0.026**	**X29(-1)**	**0.009**
X30(-6)	-0.008	X32(-1)	0.019	X28(-1)	0.003	X25(-3)	-0.015	**X26(-5)**	**-0.003**	**X27(-5)**	**-0.004**	X29(-1)	0.006	X28(-1)	0.002	X35(-6)	-0.003	**X29(-6)**	**0.011**	**X30(-4)**	**-0.003**	**X29(-6)**	**0.014**	**X29(-4)**	**-0.028**
X32(-1)	0.022	X32(-2)	-0.016	X28(-6)	-0.004	**X26(-4)**	**-0.002**	**X27(-5)**	**-0.004**	X28(-1)	0.002	X29(-4)	-0.018	X29(-1)	0.006			**X30(-4)**	**-0.002**	**X32(-1)**	**-0.009**	**X30(-4)**	**-0.004**	**X29(-6)**	**0.016**
X32(-2)	-0.020	X33(-5)	0.002	X29(-1)	0.007	**X27(-4)**	**-0.003**	X28(-1)	0.002	X29(-1)	0.007	X29(-6)	0.008	X29(-4)	-0.017			**X32(-1)**	**-0.016**	**X32(-5)**	**0.012**	**X32(-1)**	**-0.011**	**X30(-4)**	**-0.003**
X33(-1)	0.013	X35(-1)	0.004	X29(-4)	-0.016	X28(-1)	0.004	X29(-1)	0.007	X29(-4)	-0.019	X30(-1)	0.008	X29(-6)	0.008			**X32(-3)**	**0.019**	X33(-5)	0.021	**X32(-5)**	**0.014**	**X32(-1)**	**-0.017**
X33(-6)	-0.011	X35(-6)	-0.007	X29(-6)	0.008	X28(-6)	-0.004	X29(-4)	-0.019	X29(-6)	0.009	X30(-6)	-0.011	X30(-1)	0.008			X33(-4)	0.015	X33(-6)	-0.020	X33(-4)	0.016	**X32(-3)**	**0.021**
X34(-1)	-0.007			X30(-1)	0.006	X29(-1)	0.008	X29(-6)	0.009	X30(-1)	0.010	X32(-5)	0.004	X30(-6)	-0.011			X33(-6)	-0.013	X34(-1)	0.010	X33(-6)	-0.015	X33(-4)	0.014
X34(-5)	0.007			X30(-6)	-0.010	X29(-4)	-0.018	X30(-1)	0.009	X30(-5)	-0.014	X34(-4)	-0.003	X32(-5)	0.004			X34(-1)	0.010	X34(-4)	-0.013	X34(-1)	0.010	X33(-6)	-0.013
X35(-3)	0.006			X32(-1)	0.002	X29(-6)	0.009	X30(-6)	-0.013	X32(-5)	0.003	X35(-3)	0.003	X34(-4)	-0.003			X34(-4)	-0.012	X35(-1)	0.003	X34(-4)	-0.013	X34(-1)	0.010
X35(-6)	-0.008			X33(-2)	0.002	X30(-1)	0.007	X32(-5)	0.003	X34(-6)	-0.003	X35(-6)	-0.004	X35(-2)	0.003			X35(-2)	0.003	X35(-6)	-0.003	X35(-6)	-0.002	X34(-4)	-0.013
				X35(-1)	0.005	X30(-6)	-0.011	X34(-6)	-0.002	X35(-3)	0.004			X35(-6)	-0.004			X35(-6)	-0.004					X35(-1)	0.004
				X35(-6)	-0.007	X33(-6)	0.002	X35(-3)	0.005	X35(-6)	-0.005													X35(-4)	-0.005
						X35(-3)	0.006	X35(-6)	-0.007																
						X35(-6)	-0.007																		

Table 5.11 Thailand: Weights of disaggregate indicators

00M6		01M6		02M6		03M6		04M6		05M6		06M6		07M6		08M6		09M6		10M6		11M6		12M6	
X2(-1)	0.005	X4(-1)	-0.021	X4(-1)	-0.015	X4(-1)	-0.013	X4(-1)	-0.013	X4(-1)	-0.013	X4(-1)	-0.013	X4(-1)	-0.013	X9(-5)	0.015	X3(-2)	0.010	X2(-1)	0.005	X2(-1)	0.006	X2(-1)	0.006
X2(-5)	-0.010	X4(-5)	0.020	X4(-5)	0.014	X4(-5)	0.013	X4(-5)	0.012	X4(-5)	0.012	X4(-5)	0.013	X4(-5)	0.013	X9(-6)	-0.015	X3(-3)	-0.011	X2(-4)	-0.005	X2(-4)	-0.006	X2(-4)	-0.006
X2(-6)	0.009	X9(-5)	0.027	X9(-5)	0.023	X13(-5)	0.029	X9(-5)	0.019	X9(-5)	0.017	X9(-5)	0.016	X9(-5)	0.015	X13(-5)	0.047	X6(-1)	0.013	X3(-2)	0.010	X3(-2)	0.010	X3(-2)	0.011
X4(-1)	-0.025	X9(-6)	-0.027	X9(-6)	-0.022	X13(-6)	-0.031	X9(-6)	-0.018	X9(-6)	-0.016	X9(-6)	-0.015	X9(-6)	-0.014	X13(-6)	-0.049	X6(-2)	-0.011	X3(-3)	-0.011	X3(-3)	-0.011	X3(-3)	-0.011
X4(-5)	0.024	X11(-1)	0.004	X11(-1)	0.003	X15(-2)	0.004	X13(-5)	0.042	X12(-1)	-0.013	X12(-1)	-0.014	X11(-1)	0.002	X15(-2)	0.004	X13(-5)	0.032	X6(-1)	0.013	X6(-1)	0.013	X6(-1)	0.013
X9(-5)	0.033	X13(-5)	0.036	X13(-5)	0.027	X18(-4)	-0.008	X13(-6)	-0.045	X12(-2)	0.014	X12(-2)	0.014	X12(-1)	-0.015	X18(-3)	0.006	X13(-6)	-0.033	X6(-2)	-0.011	X6(-2)	-0.011	X6(-2)	-0.011
X9(-6)	-0.032	X13(-6)	-0.037	X13(-6)	-0.029	X18(-5)	0.007	X15(-2)	0.004	X13(-5)	0.047	X13(-5)	0.048	X12(-2)	0.015	X18(-4)	-0.007	X15(-1)	-0.004	X15(-1)	-0.004	X11(-2)	0.002	X15(-1)	-0.004
X12(-1)	-0.019	X25(-1)	0.021	X15(-2)	0.003	X25(-1)	0.036	X18(-4)	-0.008	X13(-6)	-0.049	X13(-6)	-0.050	X13(-5)	0.042	X19(-1)	0.002	X15(-2)	0.004	X15(-2)	0.004	X13(-3)	0.034	X15(-2)	0.004
X12(-2)	0.020	X25(-2)	-0.021	X25(-1)	0.021	X25(-2)	-0.060	X18(-5)	0.007	X15(-2)	0.003	X15(-2)	0.003	X13(-6)	-0.043	X27(-4)	-0.003	X21(-1)	0.004	X18(-2)	-0.006	X13(-4)	-0.036	X18(-2)	-0.005
X13(-5)	0.038	X28(-1)	0.009	X25(-2)	-0.022	X25(-3)	0.025	X19(-1)	0.006	X18(-4)	-0.008	X18(-4)	-0.008	X15(-2)	0.005	X28(-1)	0.002	X21(-5)	-0.004	X18(-3)	0.005	X15(-1)	-0.004	X18(-3)	0.004
X13(-6)	-0.040	X28(-5)	-0.009	X28(-1)	0.010	X28(-1)	0.011	X19(-2)	-0.006	X18(-5)	0.007	X18(-5)	0.006	X15(-3)	-0.003	X29(-3)	0.023	X24(-4)	-0.002	X21(-1)	0.004	X15(-2)	0.004	X21(-1)	0.004
X25(-1)	0.030	X32(-4)	0.023	X28(-5)	-0.010	X28(-5)	-0.011	X25(-1)	0.039	X19(-1)	0.005	X19(-1)	0.005	X18(-4)	-0.008	X29(-4)	-0.023	X27(-4)	-0.003	X21(-5)	-0.004	X18(-2)	-0.006	X21(-5)	-0.004
X25(-2)	-0.031	X32(-5)	-0.044	X32(-5)	-0.018	X32(-4)	0.031	X25(-2)	-0.066	X19(-2)	-0.005	X19(-2)	-0.005	X18(-5)	0.006					X27(-4)	-0.003	X18(-3)	0.005	X26(-1)	0.005
X32(-4)	0.026	X32(-6)	0.022	X32(-6)	0.018	X32(-5)	-0.061	X25(-3)	0.027	X25(-1)	0.038	X25(-1)	0.037	X25(-1)	0.037					X29(-3)	0.017	X21(-1)	0.004	X26(-4)	-0.006
X32(-5)	-0.049					X32(-6)	0.031	X28(-1)	0.010	X25(-2)	-0.063	X25(-2)	-0.059	X25(-2)	-0.059					X29(-4)	-0.019	X21(-5)	-0.004	X27(-1)	0.004
X32(-6)	0.024							X28(-5)	-0.010	X25(-3)	0.024	X25(-3)	0.021	X25(-3)	0.021					X34(-3)	0.015	X24(-5)	-0.002	X27(-4)	-0.006
								X29(-2)	-0.027	X27(-4)	-0.003	X27(-4)	-0.003	X27(-4)	-0.003					X34(-4)	-0.016	X27(-4)	-0.003	X29(-3)	0.019
								X29(-3)	0.060	X28(-1)	0.009	X28(-1)	0.007	X28(-1)	0.007							X29(-3)	0.019	X29(-4)	-0.021
								X29(-4)	-0.034	X28(-5)	-0.008	X28(-5)	-0.006	X28(-5)	-0.006							X29(-4)	-0.020	X34(-3)	0.014
										X29(-2)	-0.026	X29(-3)	0.024	X29(-3)	0.024							X32(-2)	-0.015	X34(-4)	-0.016
										X29(-3)	0.059	X29(-4)	-0.025	X29(-4)	-0.025							X32(-3)	0.017		
										X29(-4)	-0.034	X30(-1)	0.024	X30(-1)	0.024							X34(-3)	0.014		
												X30(-2)	-0.024	X30(-2)	-0.024							X34(-4)	-0.016		

Table 5.12 Non-constant indicators in the two representative rounds

Update ends[116]	00M7-01M6	01M6-02M6	08M7-09M6
SG	US: X8,X20, **X29**,**X32**,**X34** JP: X4, **X14**		**X2,**X3,**X4**,X6,X13,**X14**,**X16**,X19,X20,**X21**,X23,X24,X25,**X28**,**X30**,X31,**X32,X33,X34,X35** (20 in total)
KOR		US: X8,X16,**X19**,**X25**,X30 UK: X7,X20,X29 JP: X4	X3,X4,X7,**X8**,**X10**,**X12**,**X13**,**X16**,**X18**,**X19**,X20,**X21**,**X22**,**X23**,**X25**,**X28**,**X29**,**X30**,**X32**,**X35** (20 in total)
TW	X5,**X6**,X7,X8,X10,X13,**X14**, **X19**,**X21**,**X25**,**X26**,**X27**,**X28**,**X29**,X30,**X33**, X35		X1,**X2**,**X4**,X5,**X10**,X11,X12,X13,**X18**,**X19**,X20,X24,**X25**,**X28**,**X29**,**X30**,**X32**,**X35** (18 in total)
TH	X2,**X11**,X12,X28		X4,X11,X12,**X15**,X18,X25,**X28**,X30

Note: Indicators in bold letter refer to the second and third shifts in survival for M—.

[116] The column header refers to the update ends. For example, 00M6–01M6 refers to the adjacent updates of RDS FCIs at 00M6 and 01M6, namely, the 1st and 2nd rounds.

Table 5.13 In-sample significant Market Misalignment types and indicators

	More significantly survived Market MisalignMent types	
update ends[117]	02M6-07M6	09M6-12M6
SG	BE,CIP,GOV,Bank,MRate,**S&P**, MB, **Deriv,** Rrate, **HPEP**	BE,CIP,ECPI,GOV,Bank, **S&P,**TED,MB, **Deriv,**Rrate,HPEP
KOR	BE,CIP,ECPI,GOV,Bank,**TED,**MB,**Deriv,**Rrate, HPEP	BE,CIP,ECPI,GO**V,**Bank,TED,**MB,Deriv,**Rr**ate**,HPEP
TW	~	BE,CIP,ECPI,GOV,Bank,**TED, Deriv,MB,Deriv,**R**rate,**HPEP
TH	Not listed[118]	Not listed
	More significantly survived indicators[119]	
update ends	02M6-07M6	09M6-12M6
SG	X1,X4,X5,**X12,**X13,**X14,**X22,**X26,X27**,X29,X30,X31,X**32**	X1,X5,X6,X7,X9,X12,X13,X**18**,X**19**,X21,X23,**X26,X27**,X**29**,X31,X**32**,X33
KOR	X4,X5,X9,**X12,**X13,**X19**,X**25**,**X26,X27,**X29,X**30**	X2,X3,X5,X9,X13,X18,**X18**,X**19**,X21,**X22,X23,X24,X25,X26,X27,X28,**X**29**,**X30,**X**32,**X33
TW	X4,X5,X9,**X12,**X13,**X19**,X**25**,**X26,x27**,x29,x**30**	X3,X9,X2**0**,X2**1**,**X22,X24,X25,X26,X27,X28,**X**29**,**X30,**X**32**,X33,X35
TH	X4,x9, ,x25,x31,x35	X28, X35

Note: The variables all in bold are those level forms that survived; the indicator with only its numbered part bold indicates both of its level and differenced form survived.

[117] Similar to Table 12, the column header refers to the update ends but with different meaning. For example, 02M6–06M6 refers to the continuous update of RDS–FCIs at 02M6, 03M6, 04M6, 05M6, and 06M6, namely, the 3rd to 7th rounds.
[118] Since not many indicators successfully survived in case of Thailand and they are rather scattered in terms of market misalignment types, they are not listed.
[119] In terms of more significantly survived indicators, the differenced indicators with coefficients (differenced weights) larger than 0.01 in most of the rounds are recorded.

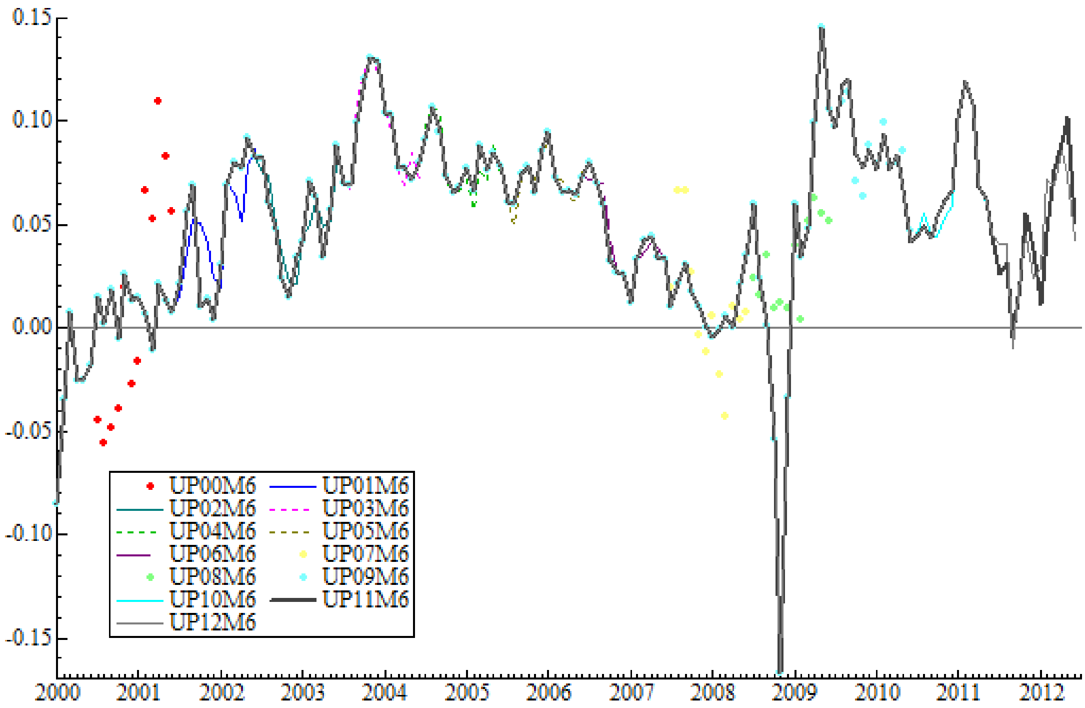

Figure 5.1 Concatenated RDS–FCIs of all 12 updates for Singapore

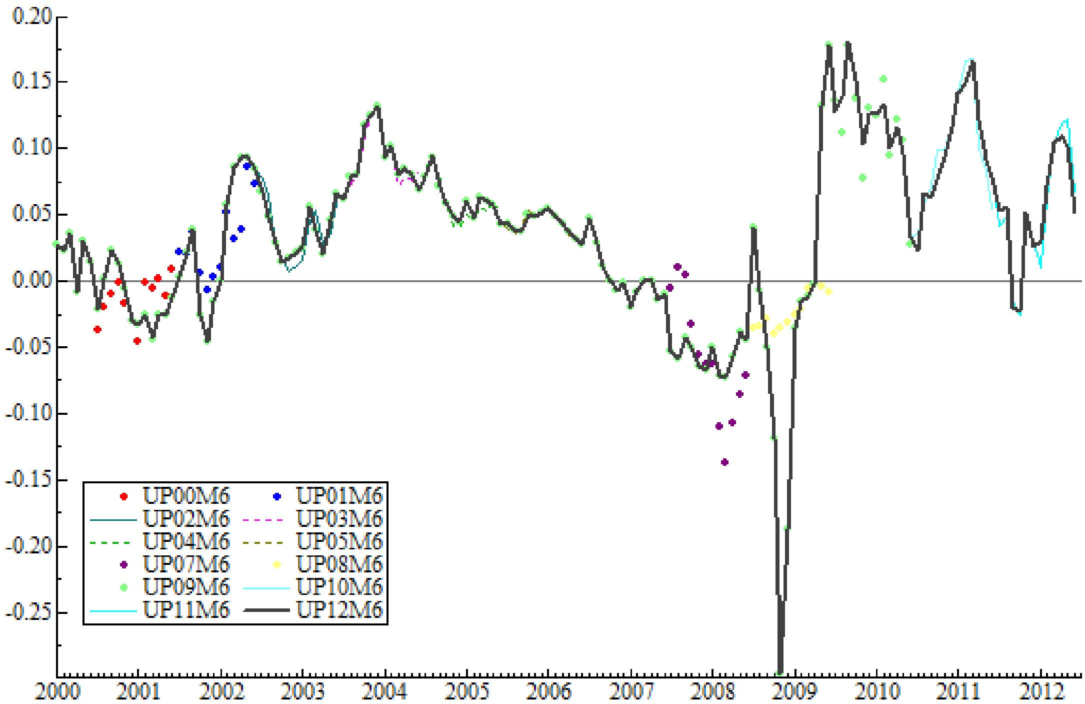

Figure 5.2 Concatenated RDS–FCIs of all 12 updates for Korea

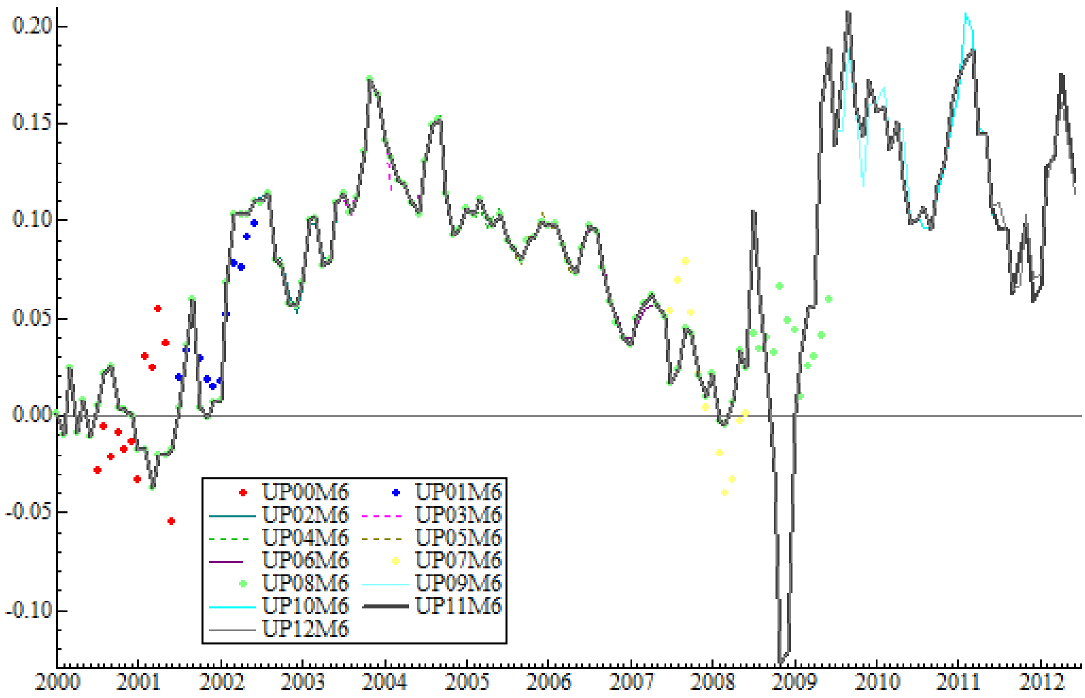

Figure 5.3 Concatenated RDS–FCIs of all 12 updates for Taiwan

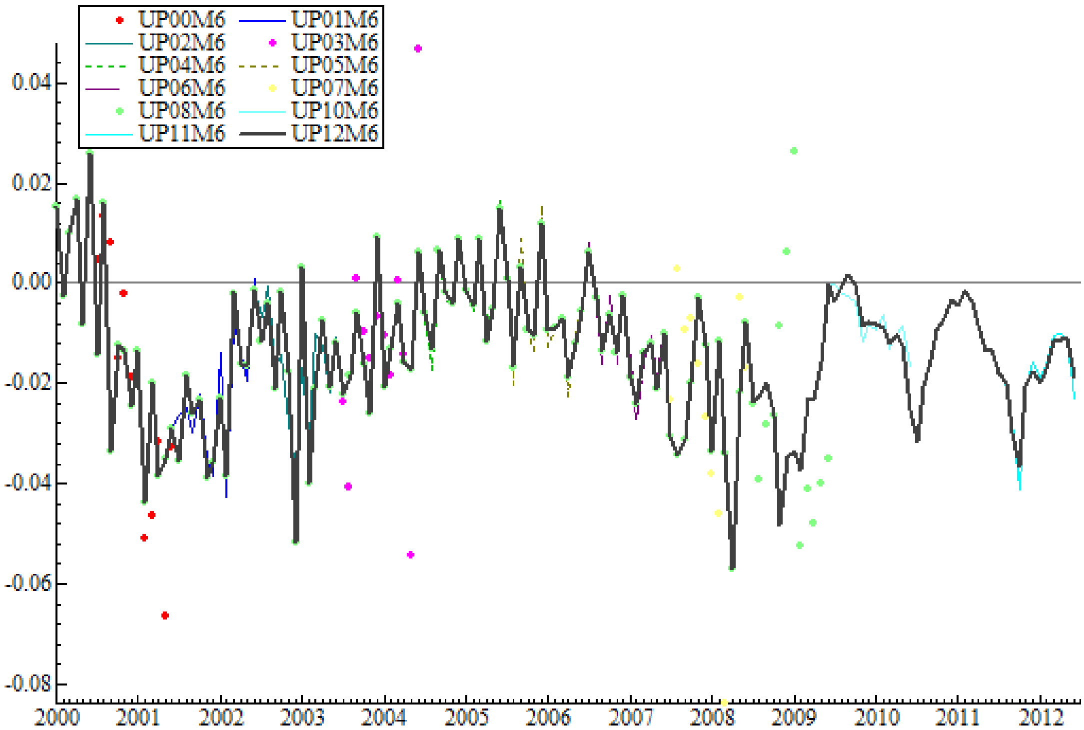

Figure 5.4 Concatenated RDS–FCIs of all 12 updates for Thailand

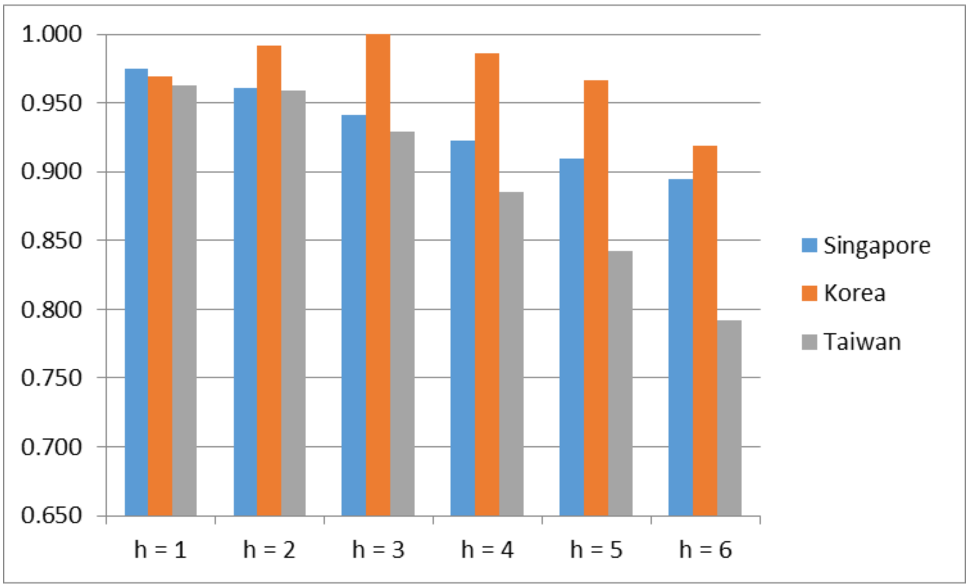

Figure 5.5 Trend of CRRMSE with different forecasting horizon

Chapter 6 Conclusions and Future work

This thesis seeks to construct international financial conditions indexes (FCIs) that can predict the import price indexes of six Asian-Pacific economies. Successive experiments on a data set (of disaggregate financial indicators) proposed by Qin and He (2012) were carried out from Chapter 2 through Chapter 5. The following concluding remarks are organized in regards to: (1) the aggregate predictive power of FCIs constructed in different ways from Chapter 2 to Chapter 5; and (2) the disaggregate predictive power of financial indicators; and (3) from the perspective of the experimental design that increasingly focuses on the practicality of FCIs. General findings are summarized.

6.1 The aggregate predictive power of FCIs

Ex ante FCIs estimated by the Dynamic Factor Model (DFM) are constructed in Chapter 2. When compared to a meticulously designed benchmark model, which includes trade-related variables as macro predictors, DFM FCIs cannot improve the forecasting performance with respect to Thailand or Malaysia. Although it is postulated that the comparatively low degree of openness of the financial sectors in these two economies explains why their DFM FCIs fail, an additional adverse finding puts FCIs estimated by DFM into question.

Specifically, both long-run and short-run FCIs are frequently found to be in-sample significant in differenced form and with long lags across the six target economies. These two specifications are counter-intuitive, because (1) level long-run FCIs should have satisfactory predictive power because of their dynamic match with the macro target, as argued by QH; and (2) it defies common sense that FCIs, especially the short-run FCIs, can be leading as far as much 6 months.

These two counter-intuitive specifications of FCIs' forecasting models, combined with their forecasting failure for the target economies of Thailand and Malaysia, led to further experimentation in this thesis on FCIs that were estimated by an alternative method, to determine whether they could enter into the forecasting model in forms fitting to common sense and/or having superior predictive power against the benchmark model for all six target economies.

Therefore, a new method, PLS regression (PLS-R) was proposed in Chapter 3 to construct FCIs. It enabled us to customize weight estimates by the characteristics of the chosen target. In addition, the in-sample weight estimates were held fixed for the entire out-of-sample period. Furthermore, by respectively targeting the import price index and the residuals of the benchmark model, two types of PLS-R FCIs were constructed—PLS-R y-predicted and PLS-R r-predicted FCIs. The modified experimental design yielded the following key findings: (1) PLS-R r-predicted FCIs are consistently better than the benchmark model, a finding that shows the superiority of PLS-R r-predicted FCIs against PCA FCIs; and (2) the forecasting failure of PLS-R r-predicted and y-predicted FCIs is larger than that of PCA FCIs. This is because PLS-R r-predicted and y-predicted FCIs basically survive in level form and therefore possibly experienced a large location shift during the 2008 crisis, while PCA FCIs basically survived in differenced form and therefore had only a small location shift.

PLS-R was revised by the Simple Dynamic Sparse method in Chapter 4. SDS–PLS can model desynchronized disaggregate dynamics and was therefore postulated to have better forecasting power than PLS-R y-predicted and r-predicted FCIs. Additionally, a concatenation method was used in Chapter 4. It allowed weights to be updated on annual basis with the expectation of better predictive power than PLS-R y-predicted and r-predicted FCIs. The empirical findings supported the postulation by showing that (1) CSDS (Concatenated SDS)–PLS are better predictors than PLS-R y-predicted and r-predicted FCIs; and (2) based on the largely expanded out-of-sample period, that is, from 07M5–13M9 (Chapter 3) to 00M7–13M6 (Chapter 4), and successive 1-year out-of-sample encompassing testing, (from 00M7–01M6 to 12M7–13M6), CSDS–PLS FCIs were found to be better than the benchmark model for most of the out-of-sample intervals. Regarding a few out-of-sample intervals that CSDS-PLS FCIs underperformed the benchmark model, large location shifts were observed. These shifts appear to have concurred with major events of the region, such as the prolonged ACC effect, China's entry into the WTO, and the 2008 crisis.

PLS-R was alternatively revised by the Revised Dynamic Sparse method in Chapter 5. RDS–PLS is equivalent to the parsimonious Finite Distributed Lag (FDL) model in the sense that the targeted import price index is regressed on lags of each of the financial indicators to estimate weights in level forms. The flexibility in modelling disaggregate dynamics by RDS–PLS leads to better forecasting performance. Specifically, CRDS–PLS FCIs outperform both CSDS–PLS FCIs and the benchmark model for most of the out-of-sample intervals. As to the few out-of-sample intervals that CSDS–PLS FCIs underperform the benchmark model, CRDS (Concatenated RDS)–PLS underperforms both CSDS–PLS and the benchmark model. Since CRDS–PLS FCIs more frequently survive in the level form, but CSDS–PLS FCIs more frequently survive in differenced form in the final forecasting models, the location shift again can be used to explain the inferiority of CRDS–PLS FCIs against CSDS-PLS FCIs.

6.2 The disaggregate predictive power of financial indicators

The disaggregate analysis in Chapter 2 was largely different from that in Chapter 3, Chapter 4, and Chapter 5. In Chapter 2, financial indicators were pre-classified according to their dynamics before aggregating into FCIs. As a result, Chapter 2 showed that the separated FCIs aggregated from the four, pre-classified separate indicator sets—long-run, monthly short-run, quarterly short-run, and annual short-run indicator sets—outperformed mixed FCIs aggregated from three mixed indicator sets—long-run financial indicators, respectively, mixed with monthly short-run, quarterly short-run, and annual short-run indicators. In addition, Chapter 2 also pointed out that FCIs aggregated from long-run indicators are more susceptible to location shift than those aggregated from short-run indicators, because location shift occurring with non-stationary original financial variables is largely differenced out when these financial variables are differenced to become stationary short-run indicators. In first part of Chapter 3, I sought to further separate the long-run indicator set from the other three short-run indicator sets and, respectively, aggregated from the long-run indicator set and any one of the short-run indicator sets. This experiment was based on the argument of QH that long-run indicators should have better forecasting performance than short-run indicators because of a dynamic match between long-run indicators and a macro target. Empirical findings generally supported QH’s argument throughout all of the six target economies.

From the second part of Chapter 3 onwards, by focusing on the long-run indicator set, the disaggregate analysis relied on the customization of weight estimates by PLS. Specifically, PLS takes the characteristics of a target economy, one of the six target economies selected in this thesis, into account when estimating the weights of indicators.

Among all long-run financial indicators, which measure different market misalignment types:

- Chapter 3 showed that weight estimates of the TED spread, along with money–inflation rate ratio and money–bond interest rate ratio are larger than average.
- Weight estimates of derivative indicators are also larger than average.
- Chapter 4 supported the disaggregate findings in Chapter 3, in that weight estimates of the TED spread were significant post-2008 crisis, and derivative indicators were significant during the whole out-of-sample period. In addition, the leading degree of derivative indicators was above the average due to the modelling of desynchronized disaggregate dynamics by SDS. In Chapter 4, it was also found that housing–equity price ratios are significant in constructing CSDS–PLS FCIs with respect to Korea and Taiwan, but not for Singapore and Thailand.

- In Chapter 5 it was also shown that, by the CRDS–PLS method, weight estimates of the TED spread and derivative indicators were significant. Specifically, the TED spread, both in the level form and in the differenced form, were significant throughout the whole out-of-sample period; derivative indicators were leading, constant throughout successive weight updating, and significantly survived in the level form. Housing–equity price ratios significantly survived in the differenced form with respect to Korea and Taiwan, they were restricted to the level form only by CSDS–PLS method.

The survival of the TED spread from Chapter 3 to Chapter 5 verifies the findings by Aramonte et al. (2013) and Koop and Korobilis (2014) that the TED spread may contribute significant predictive power in *ex ante* FCIs. The survival of derivative indicators in a much leading level form reflects the nature of derivative indicators—they are diversified products in forms of futures and options markets that can cover a large range of underlying macro economies, and they should provide more accurate and more leading prediction.

The introduction of the economic backgrounds of the six target economy, especially their differences in degrees of openness among the different target economies, helps to explains how the disaggregate findings could apply to the three developed economies—Singapore, Korea, and Taiwan, but not to Thailand. For example, weight estimates of derivative indicators are insignificant for Thailand but significant for the other three economies; the weight estimates of housing–equity price ratios are significant with respect to Korea and Taiwan, but insignificant for Thailand. At the extreme, by allowing all lags of a single financial indicator to drop out when aggregated into FCIs, CRDS–PLS has the most financial indicators drop out with the remaining ones significant, but with small weight estimates for Thailand, and the number of survived financial indicators much larger with respect to Singapore, Korea, and Taiwan.

6.3 From the perspective of the experimental design

Due to the impractical experimental designs used in the past FCIs studies (see Section 1.4), this thesis seeks to construct practical FCIs by gradually modifying the experimental design:

- In order to facilitate the understanding of the components of FCIs, this thesis attempts to shrink the size of disaggregate financial indicators that are used to construct FCIs. The disaggregate financial indicators were pre-classified according to their difference in dynamics. As a result, FCIs constructed from separate sets of long-run and short-run indicators were first shown to be superior against those constructed from a mixed set of long-run and short-run indicators in Chapter 2. Then FCIs constructed only from long-run indicators were shown be superior against those constructed only from short-run indicators in Chapter 3.

- In addition to the pre-classification method, this thesis seeks to investigate the weight estimates and update the weight estimates. In Chapter 3, a once-for-all weight-fixing approach was used in order to facilitate the understanding of disaggregate dynamics; in Chapters 4 and 5, a concatenation method was proposed for the same purpose but to allow FCIs to be updated on an annual basis. Besides the merit in facilitating disaggregate dynamics, the weight-fixing and concatenation methods both assumed historical-invariant FCIs like a real economic variable. As a result, this thesis found that the concatenated RDS–PLS FCIs outperform the concatenated SDS–-PLS FCIs, the latter of which again outperform once-for-all fixed-weighted PLS-R FCIs.
- The determination of the number of PCA–DFM/PLS factors[120] is crucially important because on the one hand, Chapter 5 showed that, in a ‘merged’ single FCI context, the interpretation of FCIs is convenient and has more significant statistical power in disaggregate analysis when only the first factor is used; on the other hand, Chapters 2 and 4 argued that the first three factors may all contain important predictive information, and the drop-off of the second and third factors may imply a large information loss. The trade-off is under scrutiny in this thesis. In Chapter 2, the first three DFM factors are used to construct FCIs based on a statistical criterion proposed by Onatski (2009); then in Chapter 3, only a single PCA and PLS-R factor are, respectively, used to construct FCIs based on the issue of practicality (Gadanecz and Jayaram [2009]); in Chapter 4, the first three SDS–PLS factors are again used to the test a postulation that the PLS-R revised by SDS may be able to reduce the high-dimensional space of financial indicators into a few factors that entail important predictive information. Finally, a single RDS–PLS factor is used to construct FCIs in Chapter 5 in order to increase the statistical power in disaggregate analysis. As a result, this thesis finds that a single (concatenated) RDS–PLS factor provides the best trade-off.

6.4 Future work

First, it is found in this thesis that FCIs contribute extra marginal predictive power to the import price index, based on an ARDL benchmark model, which includes macro predictors of major predictive power. The finding reorients future studies towards the research on where FCIs should be plugged into in structural macroeconometric models, rather than repeatedly on the

[120] Either one or three in this thesis.

predictive power of FCIs based on an AutoRegressive benchmark model that is commonly seen in the FCIs literature. Taking the forecasting practice of this thesis as an example, it is fruitful to construct FCIs that can improve the forecasting of major trade-related macro predictors, such as the domestic export price index and exchange rate. In a more general framework, the future work should be guided by the Structural Equation Modelling (SEM) practice in a causal-predictive context (Wold 1954). To put it another way, FCIs should be targeted on macro variables that are known to have relatively close links with financial markets.

Second, this thesis uses a new method, PLS, to improve the forecasting performance of FCIs, compared to the commonly used PCA–DFM method. Unlike PCA–DFM, PLS is still an explorative tool in econometric research (see Chapter 1). This thesis seeks to modify the PLS by Simple Dynamic Sparse and Revised Dynamic Sparse in order to model disaggregate dynamics to the most extent. However, the two modifications are still at a relatively primitive stage. It could be much rewarding to more flexibly use the formative mode of PLS Path Modelling methodology to model the disaggregate dynamics than a simple variant of the formative mode of PLS Path Modelling methodology that this chapter adopts, the RDS–PLS.

Third, the PLS method can be used to estimate weights of imported items that form the core import price index. As Koech and Wynne (2013, xx) argued, some imported items 'were seen as providing little or no information about the evolution of the inflation over the longer horizons'. Core import price index, therefore, is aggregated without these imported items. Koech and Wynne (2013) adopted a widely used, limited-influence estimator for the estimation of core import price index (see also Bryan et al. [1991]; Bryan and Cecchetti [1994]). They ranked the change of price of each imported item and trimmed out the most and least volatile imported items. Next, they used the remaining imported items to aggregate the core import price index. The PLS algorithm may provide a more useful estimator than the limited-influence estimator. Specifically, the weight of each imported item is estimated by the time-wise correlation of inflation with each imported item. And those imported items with insignificant weight estimates are providing little information about the evolution of the inflation.

Glossary

Term	definition
Long-run indicators	Long-run Indicators are the spread, or the ratio, of two financial variables to two different financial markets
Short-run indicators	Short-run indicators are the difference or the growth rate transformation of a single financial variable
***Ex ante* forecasting**	Neither the actual data of regressors nor regressand are allowed to be used in the out-of-sample period in *ex ante* forecasting
***Ex post* forecasting**	Both the actual data of regressors and regressand are allowed to be used in the out-of-sample in *ex post* forecasting
PLS-R	PLS-R is the abbreviation of Partial Least Squares Regression.
PLS-R y-predicted FCIs	In implementing the PLS regression approach to estimate weights of FCIs, the target variable is the import price index.
PLS-R r-predicted FCIs	In implementing the PLS regression approach to estimate weights of FCIs, the target variable is the residual of a benchmark forecasting model.
MDM	MDM statistics are derived from mean squared forecasting error and widely used for forecasting evaluation. It is first proposed by Harvey et al. (1998).
Concatenation	Concatenation is specifically referred to as a way to construct FCIs with weights regularly

	updated.
SRRMSE	In the concatenation process, SRRMSE statistics is the abbreviation of the ratio of rooted mean square error in regards to each weight-update window.
CRRMSE	In the concatenation process, CRRMSE statistics is the abbreviation of the ratio of rooted mean square error in regards to cumulative weight-update window.
P-SRRMSE	P-SRRMSE is the p-value of the SRRMSE statistics
P-CRRMSE	P-CRRMSE is the p-value of the CRRMSE statistics
Shift-constancy matching pattern	Shift-constancy matching pattern refers to the phenomenon that when a location shift of FCIs is observed in a certain weight-update window, non-constant weight estimate is also observed and vice versa.
SDS	SDS is the abbreviation of Simple Dynamic Sparse, which is used to modify partial least squares in order to reflect desynchronized dynamics
RDS	RDS is the abbreviation for Revised Dynamic Sparse. It develops from SDS and can reflect desynchronized dynamics more flexibly.

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