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Modelling the impact of aggregate financial shocks external to the Chinese economy

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Contents

Abstract.......... 4

1 Introduction 5

2 Construction of FCIs external to the Chinese economy.......... 6

2.1 Selection and classification of financial variables.......... 6

2.2 Econometric method.......... 9

3 Evaluation of the predictive power of indices.......... 11

3.1 Specification and testimation of the FCI-led forecasting model 12

3.2 Testimation experiments with other FCIs.......... 16

3.3 Predictive content of the FCI-led models 17

4 Discussion and conclusions.......... 19

References 23

Appendix: Variable definitions and data sources.......... 26

Tables and figures.......... 31

Duo Qin and Xinhua He*

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Abstract

Ways of extracting financial condition indices (FCI) are explored and alternative FCIs external to the Chinese economy are constructed to model their predictive content. The exploration aims at highlighting the rich and varied dynamic features of financial variables underlying FCIs and the importance of synchronising dynamic information between FCIs and the real-sector variables to be forecasted. The modelling experiment aims at improving the forecasting model upon which the FCIs are assessed. Four variables are chosen as the likely macro channel of the FCIs affecting the Chinese economy. It is found that the FCI-led models enjoy forecasting advantages over a benchmark model in three out of the four variables, although the benchmark model is not dominated by the FCI-led models when judged by in-sample encompassing tests. The evidence indicates the increasing exposure of the Chinese economy to the global financial conditions.

Key words: financial index, dynamic factor, VAR, error correction, encompassing
JEL Classification: E17, F37, G17, C43

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1 Introduction

The Chinese economy has encountered severe tests in the global recession triggered by the 2008 US-led financial crisis. The macro impact of the crisis was felt as soon as the fourth quarter of 2008 when the year-on-year GDP growth rate dropped to 6%, more than half of the previous year's figure – 13% in 2007Q4 – in spite of the fact that the external exposure of the Chinese financial sector was limited due to various capital control policies. As the global recession and financial turmoil prolong, the issue of how to assess, monitor and forecast effectively the aggregate impact of the external financial conditions to the Chinese economy has reached the top of research agenda, e.g. see Xue and He (2010), Yuan *et al* (2010) and also Fidrmuc and Korhonen (2010).

Meanwhile, the adverse global economic conditions in the wake of the financial crisis have nurtured a budding range of literature which scrutinises and re-examines the ways of quantifying the impact of the financial-sector activities on real-sector economic activities. The view has become increasingly shared that traditional macroeconomics is far from adequate in representing the financial sector mainly by interest rates and money aggregates. In particular, there has emerged a strand of empirical studies which seek to construct aggregative indices to represent aggregate financial shocks with predictive impact on the real-sector conditions, e.g. see Borio and Lowe (2004), Alessi and Detken (2009), Hatzius *et al* (2010), Ng (2011) and Holló *et al* (2012).

The present study extends this line of research with respect to the Chinese economy. A similar empirical study can be found in Osorio *et al* (2011), where a financial condition index (FCI) for the Asian economies was built and evaluated by means of its predictive power in forecasting GDP growth for a number of Asian economies, including China. The present study differs from that paper in several aspects. First and the most obvious, our FCIs are constructed for the purpose of assessing their impact on the Chinese economy, though they have the potential to be applied to other developing economies. Second, our FCIs are designed to summarise the financial conditions external to the Chinese economy, rather than its internal conditions. Third, our FCIs are evaluated by their predictive power of several macro variables which are widely known as directly sensitive to external shocks, such as exports and the aggregate import price index, rather than the commonly used single variable – GDP growth. Finally and more importantly from a methodological viewpoint, alternative methods of extracting FCIs are explored so as to highlight different dynamic properties of different financial indicators and to seek ways of improving the forecasting capacity of FCIs. Specifically, we experiment with two extensions of the commonly used modelling method. (a) Design and categorise financial indicators into different sets by their different dynamic properties and extract separate FCIs from these sets with the aim to better synchronise the spectral distributions of the FCIs with those of the target real-sector variables for forecasting. The details are described in the next section. (b) Extend the commonly used vector autoregression (VAR) model with an error-correction (EC) component and improve the model specification by the London School of Economics (LSE) general-to-specific dynamic specification approach so as to strengthen the model infrastructure upon which the predictive capacity of FCIs is to be assessed. As part of this extension, the principle of encompassing is applied to both within-sample model comparison and out-of-sample forecast evaluation. Section 3 is devoted to the description of the extension. The main findings and possible directions for future research are summarised in the final section.

2 Construction of FCIs external to the Chinese economy

The existing FCIs are constructed broadly under two approaches: a weighted-sum approach and a factor model-based approach, see Hatzius *et al* (2010). Their paper also contains a relatively comprehensive literature survey. FCIs built by the first approach enjoy the advantage of easy interpretability while the primary motive underlying the second approach is to raise the predictive power of FCIs. Since the same motive is shared by the present investigation, the second approach is adopted here. Before the detailed modelling method is discussed, however, the selection of financial variables as components of the indices is described first.

2.1 Selection and classification of financial variables

As in recent literature, the range of financial variables for consideration includes both the traditionally banking-sector based variables, such as interest rate and aggregate money, and non banking-sector based variables representing the general conditions of financial markets, such as equity and futures market indices, bond yields and various term spreads. The latter part is selected with reference to the financial concepts discussed by Ng (2011).

Geographically, the variables are selected from Japan, the USA, the UK and the euro area. Data from France and/or Germany are used as substitutes when euro area aggregates are unavailable. A general criterion of selection is that the coverage is to be as comprehensive as possible while variables with largely overlapping information should be avoided. Data of the selected variables are in monthly time series, starting from 1990M1 whenever possible.

Most of the selected variables are in need of certain transformations before they could be used as indicators for the extraction of indices or common factors. If one scans through the indicators used for the extraction of various existing FCIs, the transformations fall roughly into two categories. The first is made up of combinations of variables, such as interest rate spreads and various ratios. The second covers time-wise transformations of single variables into growth rates or differences. Transformations of the latter type are not unique in that they could either be taken over a one-month, three-month, one-year span, or even longer spans such as those being detrended by 2–4-year moving averages. Noticeably, choice of the time span will affect the dynamic properties of the indicators and consequently the dynamic properties of the factors to be extracted. For example, indicators made up of monthly rates generally demonstrate higher frequency volatilities than those made of annual rates. Here, recognition of these differences is important because financial variables are known to contain dynamic information of much higher volatilities than those observed in most macroeconomic variables. Disregard of such dynamic mismatch between financial indicators and the real-sector variables could easily result in the under-estimated impact of aggregate financial shocks on the real sector, e.g. see Park and Shin (2009). In the event where business cycles form the main object of research interest, the financial variables which are postulated as constituting a key driving force of business cycles should be scrutinised, particularly in term of their dynamic properties, as argued recently by Drehmann *et al* (2012).

When the dynamic properties of the indicators from the two categories are compared, it can be observed that major shocks in the indicators of the first category are scattered at a much lower frequency than those in the indicators of the second category, unless the time span for differencing of the latter indicators is set to be rather long, say 2–4 years. That is because the shocks or volatilities in the indicators of the first category represent a different type of economic phenomena – disparities between different markets and sectors pertinent to the cross-variable comparison. As such, the dynamic information contained in the indicators is widely considered as indicative of market frictions or misalignments, i.e. disequilibrium movements, and also of impending market adjustments to correct such frictions or misalignments. That is why the practical usefulness of various financial ratios has been long attended and scrutinised, e.g. see the recent discussion by Giot and Petitjean (2009).[1] Accordingly, two ways of organising the transformed indicators are experimented here for the extraction of common factors. One is the conventional way of mixing all the indicators together as one data set; the alternative is to extract separately two sets of common factors from indicators of the two categories respectively. Hereafter, we refer to FCIs extracted by the first way simply as the 'mixed' indices and the corresponding indicator sets as the 'mixed' sets, and FCIs by the second way as the 'separate' indices and the corresponding indicator sets as 'separate' sets. Within the separate sets, we refer to the indicator set of the first category as the 'long-run' set and the indicator set of the second category as the 'short-run' set.

Around 40 indicators have been considered originally for the long-run set. Over a quarter were deselected. Three criteria are used for the selection. The first is to trim multiple indicators which share close time-series patterns to a single one. The second is to remove indicators whose time series are dominantly trended within the sample without any discernible disequilibrium corrections. For instance, the ratios of the equity market indices to the futures market indices were deselected for that reason. The third is the very low factor loading from primary experiments of factor extractions. Examples of such indicators include the ratio of financial sector equity price index to the CAC-40 index of the French equity market, and also the term spread of the French government bonds, both were originally constructed as proxies for the euro area. A list of the remaining indicators of the long-run set is reported in Table 1.1.

The list of variables used in the short-run indicator set is given in Table 1.2. The table clearly illustrates that not all the individual variables covered in the long-run set are included while there are variables present which are not covered in the long-run set. The exclusion of variables which are used in long-run set is mainly due to the general selection rule of avoiding variables with highly repetitive short-run dynamic features. For example, among the money market rates, only 3-month rates are kept. The third criterion used above for the long-run set is also applied here. For example, two open interest series for both the

[1] In fact, the empirical significance of economic ratios has been recognised over half a century ago, e.g. see

futures and the options markets were initially selected but one series was later removed for each country or region because of its relatively low loading. As mentioned before, there is no unique *a priori* reason for setting the time span for time-series transformation. Therefore, three time spans are considered – monthly, quarterly and annual spans, which result in three short-run indicator sets.

To monitor the dynamic properties of indicators, periodograms of individual indicators are drawn and examined during the selection process. A sample of the raw (i.e. before standardisation) indicators and their corresponding periodograms are provided in Figures 1.1 and 1.2 respectively. Figure 1.1 illustrates the spectral distributions of the long-run indicators are clustered closely to the zero pole, indicating that their dynamic information content is dominantly on the low-frequency side. In contrast, the spectral distributions of the short-run indicators are scattered further away from the zero pole, the shorter the time span for differencing, as shown in Figure 1.2.

2.2 Econometric method

Since prediction is the key objective here, dynamic factor models (DFM) are used instead of static ones, similar to what Osorio *et al* (2011) have done. The state space representation of a DFM can be written as:

$$\begin{aligned} z_t &= \Gamma f_t + \varepsilon_t \\ f_t &= \Lambda(L) f_{t-1} + \nu_t \end{aligned} \tag{1}$$

where z_t denotes an *n*-vector of standardised indicators, f_t denotes an *m*-vector of latent common factors with $m << n$; ε_t and ν_t are vectors of error terms; Γ is a loading parameter matrix and $\Lambda(L)$ is a companion matrix of lag polynomial, and both matrices are to be estimated. The autoregressive equation of f_t in (1) renders us an expedient way to forecast the factors, which will be useful in the next section. With respect to the indicator sets described in 2.1, model (1) is run for seven different sets of z_t. The first four sets are 'separate' sets, which include the long-run set, z_t^l, and three short-run sets: $z_t^{s_1}$ (monthly), $z_t^{s_2}$ (quarterly), $z_t^{s_3}$ (yearly); the last three are 'mixed' sets: $z_t^{m_1} = \left(z_t^{s_1} \cup z_t^l\right)$,

Klein and Kosobud (1961).

$z_t^{m_2} = \left(z_t^{s_2} \cup z_t^l\right)$ and $z_t^{m_3} = \left(z_t^{s_3} \cup z_t^l\right)$. The resulting sets of factors are denoted as f_t^l, $f_t^{s_1}$, $f_t^{s_2}$, $f_t^{s_3}$, $f_t^{m_1}$, $f_t^{m_2}$ and $f_t^{m_3}$ respectively.

The Kalman filter algorithm is used to estimate (1) with the initial parameter estimates obtained via principal component analysis. Among other things, the algorithm has the advantage of handling unbalanced panel data sets. The number of factors, *m*, is determined by a test procedure developed by Onatski (2009). The lag length is chosen from experimenting with different lags up to a maximum of *L*=3. Information criteria, such as Akaike and Schwarz criteria, are used to choose the appropriate lag lengths. The result of the experiment is reported in Table 2, together with *m*, as determined by the Onatski procedure. It should be noted from Table 2 that our finding of the maximum $m = 3$ coincides with that experimented by Hatzius *et al* (2010).

Figures 2.1 and 2.2 show the time-series plots and the corresponding periodograms of the two groups of the extracted FCIs. It is discernible from Figure 2.1, as expected from Figure 1.1, that the spectrum distributions of the long-run FCIs are narrowly concentrated towards the zero pole, indicating much lower frequency information than that contained in the short-run FCIs, while the spectral locations of these short-run factors move decisively towards the zero pole with the increase of the time span for differencing. What is not quite expected is that, under the mixed situation, the spectrums are clustered towards the zero pole with the spectral location of the monthly case being the closest to the zero pole, as shown from the periodograms in Figure 2.2. It suggests that a mixture of indicators with different dynamic properties will not only lead to the dominance of lower frequency information at the expense of higher frequency information but also spoil the association between the order of the spectral locations and the time span for differencing applied to the short-run indicators.

To assess how much the volatilities of individual indicators have been filtered into the factors, the communality coefficients of the indicators are plotted by rank in Figures 3.1 and 3.2. A striking difference between the long-run set and the short-run sets in Figure 3.1 is that communality is much stronger and more widely shared by the indicators of the long-run set than those of the short-run sets. Moreover, communality gradually increases with the time span for differencing used in the short-run sets. In other words, indicators of the monthly set are the most heterogeneous while indicators of the long-run set are the most homogenous. These observations explain why growth-rate or differenced variables are often taken over longer than one year time spans when they are mixed with indicators of the long-run type, e.g. see Hatzius *et al* (2010). It is also seen from Figure 3.1 that, of the long-run set, ratios of equity market indices to CPI and the covered interest parity indicators are among the top-ranked indicators, while the term spreads of the money market are among the lowest in ranking. In the short-run sets, the growth rates of stock market indices occupy the front ranks, mixed with the growth rates of the futures market indices in the quarterly and annual sets; the ranks of the growth rates of most of the quantity indicators are rather low, such as those of M1, except for the open interest of the US futures market. When it comes to the mixed indicator sets, as shown in Figure 3.2, the communality coefficients of the long-run indicators dominate the front ranks, especially in the mixed-monthly set where a group of equity market rates monopolises the lead. That explains why only one factor of very low spectral frequency has been extracted from the set. Increasingly more short-run indicators move up ranks on a par with the long-run indicators as the time span for differencing increases. Hence, multiple factors have been extracted from both the mixed-quarterly and the mixed-yearly sets, and the spectral distributions of those factors contain higher frequency information than that of the mixed-monthly factor.

3 Evaluation of the predictive power of indices

The most common practice in the literature is to use the GDP growth rate as the key target variable for forecasting and a growth-rate based VAR as the forecasting model. Evaluation of the predictive power of FCIs is then carried out by comparing the root mean-squared forecast errors (RMSFE) of an FCI-led VAR with the RMSFE of a benchmark VAR where the FCIs are excluded, e.g. see Hatzius *et al* (2010) and Osorio *et al* (2011). While broadly following the above procedure, a number of steps are taken here to strengthen the common practice. These include (i) choosing different target variables, (ii) augmenting the VAR by an error-correction (EC) component to accommodate, in particular, the separate extraction of the long-run and the short-run FCIs, (iii) improving the robustness of the fitted models by the LSE general-to-specific dynamic specification approach, and (iv) evaluating model in-sample and out-of-sample performance by the principle of encompassing.

3.1 Specification and testimation of the FCI-led forecasting model

Considering the size of the Chinese economy with its limited, albeit increasing, degree of openness, it can be far-fetched to use the GDP directly as the target variable here. Therefore, four macro variables are chosen instead for their closeness to foreign trade and finance: the total exports, M1, the import price (year-on-year) index and market interest rate (3-month interbank lending rate). It is too obvious to describe the close relationship between total exports and GDP as well as between M1 and GDP. It is also well acknowledged that market interest rates have been exerting increasingly important impact on money aggregates in China. As for the import prices, their pass-through to the domestic CPI could run up to 10% and the impact of 1% import price change could induce 0.05% change in the urban private consumption, e.g. see Luo and Guo (2010). Monthly series of the total exports and M1 start from 1990M1; the monthly import price index series starts from 1993M1, and the interest rate starts from 1996M1. Since no appropriate deflators are available for the first two variables, they are modelled in the nominal term. Figure 4 presents the time-series plots and the corresponding periodograms of the four variables. It is clear from the figure that their spectrums are located on the low side, with both the export and the M1 series exhibiting distinctly the unit-root or weakly nonstationary phenomenon.

Apart from the choice of target variables, the commonly used VAR suffers from two major problems. One is the neglect of any long-run disequilibrium-correcting mechanism as a leading indicator, and the other is the well-known curse of dimensionality. Here, we circumvent the first problem by augmenting factor-model based VARs by an EC component, as explored empirically by Qin *et al* (2007a; 2008) and Qin (2008), and experimented in a more analytical setting by Banerjee *et al* (2010). Among other things, an EC-augmented VAR enjoys the practical flexibility of the EC representation in handling the disequilibrium co-movements of variables irrespective of whether they are indeed nonstationary individually. For example, the EC term would become insignificant in the event when individual variables are nonstationary but not cointegrated (i.e. the model is reduced to a VAR). As for the second problem, we adopt the LSE general-to-specific approach to reduce a dynamically generally specified model through an iterative process of model estimation and testing known as 'testimation', and reparameterise the resulting data-admissible model into a parsimonious model, e.g. see Hendry (1995; 2009). It should be emphasised that such a model reduction and reparameterisation process can help improve the model forecasting accuracy, as demonstrated by Qin *et al* (2008), see also Clements and Hendry (2002) for a more analytical discussion.

Now, suppose the FCI-led VAR in correspondence to (1) is written as:

$$\Delta y_t = \alpha_0 + \alpha(L)\Delta y_{t-1} + \beta(L) f_{t-1} + u_t \tag{2}$$

where y_t denotes a vector of the target variables, Δ denotes first difference, α_0 is a vector of intercept, $\alpha(L)$ and $\beta(L)$ are parameter matrices of lag polynomial where the minimum lag lengths are determined such that autocorrelation is absent from the error-term vector, u_t . Given that the FCIs represent the external conditions here, the above VAR has to be open with respect to f_t in that f_t are exogenous and pre-determined. The EC-augmented VAR under the conventional way of factor extraction, i.e. the mixed-factor situation, can be generally written as:

$$\Delta y_t = \alpha_0 + \alpha(L)\Delta y_{t-1} + \beta_1(L) f_{t-1}^{m_s} + \beta_2(L)\Delta f_{t-1}^{m_l} + \lambda \begin{pmatrix} y \\ f^{m_l} \end{pmatrix}_{t-1} + e_t \tag{3a}$$

Where the factor set is subdivided as $f_t^m = f_t^{m_s} \cup f_t^{m_l}$, because we cannot expect all of the factors to enter the EC term when they are extracted from a s et of mixed short-run and long-run indicators, as indicated from Figure 2.2. Under the separate-factor situation, the model naturally takes the form:

$$\Delta y_t = \alpha_0 + \alpha(L)\Delta y_{t-1} + \beta_1(L) f_{t-1}^{s} + \beta_2(L)\Delta f_{t-1}^{l} + \lambda \begin{pmatrix} y \\ f^{l} \end{pmatrix}_{t-1} + e_t \tag{3b}$$

The corresponding benchmark model can be written as:

$$\Delta y_t = \delta_0 + \delta(L)\Delta y_{t-1} + \kappa y_{t-1} + u_t \tag{4}$$

In order to make the benchmark model as comparable as possible, (4) is also put under the same general-to-specific approach to reduce it into an as parsimonious and data-admissible model as possible.

It should be emphasised that the scope of the above models are limited by the primary objective of evaluating the predictive power of the FCIs. In other words, the present modelling exercise aims at finding whether some of the estimates of $\beta(L)$ and/or λ in

(3a) and/or (3b) are statistically significant and, when confirmed, whether the estimates are relatively constant since parameter instability constitute a major threat to forecasting accuracy. Hence, possible model mis-specification owing to omitted variables is disregarded, even though the probability of having such mis-specification is rather high in view of the exclusion of other domestic variables which are intimately related to the four target variables. Nevertheless, the disregard should not seriously affect the estimated $\beta(L)$ and/or λ, thanks to the EC reparameterisation.

Table 3 reports the main results of the data-admissible and parsimoniously reparameterised models which are reduced via testimation from dynamically generally specified (3a) and (3b) (the last point of estimation is set on 2010M12, reserving the subsample period of 2011M1-2012M6 for out-of-sample forecasting). The corresponding benchmark model is also reported in Table 3. Because of the importance of parameter constancy, the Hansen instability test is carried out and reported (see the statistics given in the bottom parentheses below the standard deviations). To save space, the usual diagnostic test results are not reported. But signs of model mis-specification are detectable from those Hansen test statistics on the variance of the residual term, e.g. the case of the interbank rate equations. That confirms our earlier warning on the likely presence of the omitted-variable problem.

Nevertheless, the strength of the parsimonious EC reparameterisation against omitted-variable bias should enable us to be focused on the role of the external FCIs. In that respect, several findings are discernable from the resulting models. First, some of the FCIs have survived the reduction process in all of the four equations of both versions (3a) and (3b), and all the parameter estimates of the surviving FCIs are relatively constant, as shown from the Hensen test statistics in Table 3. During the testimation process, it is also revealed from recursive estimation that a few of the surviving FCIs did not evolve into the 95% significance band until after 2008. That may reflect the gradually increasing exposure of the Chinese economy to the external financial shocks. Secondly, EC terms have survived in all of the equations of (3a) and (3b), although the EC terms in the M1 case are weaker than expected with respect to the very small feedback coefficients.[2] It is obviously easier to attach economic explanation to those of version (3b) than version (3a) since the long-run

[2] The M1 equation is obviously mis-specified with respect to the long-run EC term, since the vital variables representing domestic transaction and opportunity demand are missing, e.g. see Qin (1994) and Qin *et al* (2005).

FCIs which enter the EC terms in (3b) represent exclusively the disequilibrium movement of the external financial conditions. Whereas under version (3a), the fact that some of the FCIs have entered the EC reparameterisation indicates that the dynamic information contained in them is a bit too slow to be interpreted as embodying short-run shocks, an aspect already shown from Figure 2.2. Thirdly, different target variables have reacted to the FCIs in different ways and degrees. For example, all the lagged domestic variables have dropped out from the import price equations, verifying the common postulate that import prices should be externally determined. In contrast, both M1 and the market interest rate show rather strong dependence on the domestic side if judged roughly by the magnitudes of the coefficients of their own lags, a finding which reflects the limited external exposure of the financial sector. Finally, it is interesting to note different short-run responses across the equations from the separate FCI case. Only the import price and interest rate variables respond to the monthly FCI; the short-run FCIs explaining M1 and exports are built from the quarterly and annual indicator sets, indicating that these two quantity variables do not react as quickly to the external financial shocks as those price variables. More interesting, all the four variables are found to be driven by short-run shocks from changes, or even accelerations, of certain long-run FCIs, revealing complicated dynamic adjustments of the modelled variables with respect to external financial market frictions or misalignments. Such information is unfortunately lost in the mixed FCI case, since there is no direct association between the time spans for differencing and the dynamic properties of the factors. Indeed, it is impossible to decide, through the EC reparameterisation there, which FCIs should be interpreted definitely as short-run shocks, since these appear both in levels and also in the differenced form.

In order to facilitate the comparison of the various model versions, in-sample encompassing tests are carried out and reported in Table 4. Noticeably from the table, none of the three models is found to be statistically dominant of the others in general. When models (3a) are (3b) are compared, the test statistics indicate that neither version can encompass each other except in the import price case, where the test results suggest mutual encompassing; when both versions are compared to the benchmark model, the mixed-FCI model is found to be superior to the benchmark model in the cases of the export equation and the M1 equation. This result may also reflect the limited direct exposure of the Chinese economy to the external financial conditions during a large part of the period covered by our data sample. Nevertheless, the lack of a discriminating verdict from the in-sample encompassing tests makes the evaluation of the predictive content of the FCIs ever more crucial and challenging.

3.2 Testimation experiments with other FCIs

Before turning to the out-of-sample forecasting exercise, let us apply the same testimation experiment on the basis of model (3a) to a number of FCIs which have been constructed by others. The experiment is desired to provide us with some comparative bearings of the explanatory power of the FCIs that we have extracted by model (1). Three sets of FCIs are collected here for the experiment. The first one is from Bloomberg and the second from the OECD (Organisation for Economic Co-operation and Development). Both are single time series constructed under the weight-sum approach (for a more detailed description of these two sets, see Hatzius *et al*, 2010). The OECD set consists of three series, one for the US, the second for Japan and the third for the euro area.[3] Since the last series is quite short, only the first two are used in our comparison experiment. The third set is from Hatzius *et al* (2010).[4] Since this set is produced by the factor-model based approach, it contains three alternative subsets – one series from a one-factor model, two series from a two-factor model and three series from a three-factor model.

When the general-to-specific testimation procedure is carried out on model (3a) using, instead, the Bloomberg FCI and the OECD indices respectively (L is set to start from four), neither set has survived the model specification reduction. Hence the detailed results are not reported here. The same is found with the first two subsets of the FCIs by Hatzius *et al* (2010). However, some of the three FCI series of the third subset have survived the model specification reduction and the key results are reported in Table 5. It is seen from the table that the equations do not fit the data as equally well as those FCI-led models reported in Table 3, and the problem of parameter instability is quite pronounced. Nevertheless, the experiment demonstrates clearly that it is probably an over-simplistic desire to confine FCIs to a single time series and achieve with it any significant predictive gain in routine forecast modelling practice.

[3] The OECD set is downloaded from the OECD 2011 Outlook. The indices are in quarterly frequency, see Guichard *et al* (2009). Simple interpolation is used to transform the indices into monthly series here.

3.3 Predictive content of the FCI-led models

As stated before, the subsample period of 2011M1-2012M6 is reserved for out-of-sample forecasts. Due to this short sample, we set the maximum forecast horizon to be six months or two quarters. Before running the full-model forecasting experiment, a single-equation Chow test and the forecast error zero-mean test are run for all three models reported in Table 3 to ensure that none of the fitted equations suffers from significant parameter shifts for the entire out-of-sample period. As seen from Table 6, all the models pass the 18-month Chow test in the first three equation cases, except for (3b) in the export equation case, and also the forecast error zero-mean test at 5%. None of the models perform satisfactorily in the M1 equation case, confirming to our earlier diagnosis that this equation suffers from omitted-variable mis-specification.[5]

In our full-model forecasting experiment, the out-of-sample values of the FCIs need to be separately forecasted, since they are exogenous in (3a) and (3b). Two sets of forecasts are produced. One makes direct use of the second equation of the DFM in (1) as the forecasting equation. The other takes into consideration of the possible correlations between factors when the number of factors is larger than one for one indicator set, i.e. the cases of f_t^l, $f_t^{m_2}$ and $f_t^{m_3}$. In such cases, 3-variable VARs are fitted and used to generate forecasts to replace those by simple autoregressive equations. These forecast results reveal some noticeable discrepancies between the forecasts and the estimated FCI values using the full-sample information. The discrepancies may be explained by the observation of frequent occurrence of parameter instability in DFMs, e.g. see Stock and Watson (2009) and Bates *et al* (2012). In other words, the DFM is poorly fitted for forecasting purposes. Hence, three scenarios are designed for the forecasting exercise – the first using the estimated FCIs and the second and the third using the two sets of predicted FCIs respectively.

Following the literature, ratios of the RMSFEs of the FCI-led models to the RMSFEs of the benchmark model are used as the basic measure of our assessment. Series of these 1-6 step ratios are plotted in Figures 5.1-5.4 by target variables. As seen from these figures, the FCI-led models demonstrate a clear forecasting advantage over the benchmark model in the import price equation case, and a certain degree of advantage in the interest rate

[4] The FCIs by Hatzius *et al* (2010) are downloadable from http://www.princeton.edu/~mwatson/publi.html . Since the series are in quarterly frequency, simple interpolation is used to transform them into monthly series.
[5] It should be noted that single-equation forecasting tests are limited by the practice of using the actual values, rather than the forecasted values, of all the explanatory variables during the forecasting period.

equation case; whereas no success is visible in the export equation case and an obvious failure in the M1 equation case. Again, the latter is not surprising from our earlier acknowledgment of the existence of significant model mis-specification there. In the import price equation case (see Figure 5.1), scenario one produces somewhat more accurate results on average, while scenario two fails to improve the forecast accuracy as compared to scenario three. But the improvement is remarkable in the case of the interest rate equation case, as shown in Figure 5.2. When the FCI-led models are shown to improve forecasting accuracy, as in the import price and interest rate equation cases, scenario one is probably the best of the three in general. Interestingly in the both cases, the mixed-FCI model results outperform those of the separate-FCI model. But that ceases to be true in the export equation case.

In order to verify whether the extra predictive power by the FCI-led models shown in some of the cases is statistically significant, a forecasting encompassing test of the FCI-led models versus the benchmark model is carried out equation by equation. The test is commonly known as the modified Diebold-Mariano (MDM) test, see Harvey *et al* (1998). The test results shown in Table 7 render a strong verdict that the benchmark model fails to encompass the FCI-led models except for the M1 equation case, in sharp contrast to the in-sample encompassing test results. In the export equation case, failures of the FCI-led models in encompassing the benchmark model have occurred mostly in scenarios two and three, indicating the importance of having timely estimated FCI values.

To better summarise our model forecast results, average series of the RMSFE ratios of all the six sets of forecasts are reported in Table 8.1, taking advantage of the method of forecast pooling, e.g. see Hendry and Clements (2004). The predictive usefulness of the FCIs is evident, especially in longer than 3-step horizons of the first three cases. The increasing gain as the forecast horizon extends is corroboratory to the EC-augmentation of the VAR. It is also interesting to find forecasting gain in the export equation case, which serves as clear evidence in support for pooling. The practical significance of such gain should go without saying. Just consider how much better we might be able to predict the direct impact on CPI by aggregate import price shocks if our forecasts of these shocks could become about 40% more accurate up to six months in advance.

However, one weakness of EC models as compared to the growth-rate based VAR model is their susceptibility to systematic forecast failures caused by equilibrium mean shifts, e.g. see Castle *et al* (2011) and Hendry (2011). In order to check against such possibilities, series of the *t*-test statistics on the error means of the pooled forecasts are produced (see Table 8.2). The same test is also run for the benchmark model (see Table 8.3). None of the *t* statistics exceeds the 5% critical value except for the M1 equation case, which verifies again our earlier inference of that equation being seriously mis-specified.

4 Discussion and conclusions

Let us summarise what we have done and learnt from this modelling exercise, and what needs to be further pursued in future search.

In this study, an extensive set of financial variables is collected from Japan, the USA, the UK and the euro area. The variables are transformed into appropriate indicators for the purpose of constructing FCIs which represent external financial shocks to the Chinese economy and are expected to exert statistically significant leading impact on the economy. The DFM approach is adopted for the construction. In order to check and avoid possible mismatches between the dynamic properties of the extracted FCIs and the macro economic variables chosen as the target variables of forecasting, an alternative way of organising the indicators is experimented and compared to the conventional way – grouping all the indicators as one dataset for the FCI extraction. By separating the indicators into a long-run set and several short-run sets, the experiment reveals distinctly different dynamic properties of the resulting FCIs. It also shows how the properties become mixed up in the FCIs extracted under the ‘mixed’ situation. These alternative sets of FCIs are then used respectively as leading-indicator variables in a forecasting model for four Chinese macro variables. The model is built to compare with a benchmark model in which the FCIs are absent following the convention. Furthermore, several steps are implemented to improve the forecasting models and also the forecasting process. The first is to augment the VAR, the most commonly used model for forecasting, by an EC component. The second is to subject the EC-augmented VARs to the LSE model specification and reduction procedure such that parsimonious and data-admissible models are produced prior to the out-of-sample forecasting exercise. The last is to assist comparison of both the in-sample model fitness and the out-of-sample forecasts by means of encompassing tests.

It is worthwhile reiterating and discussing a number of findings here, mainly from the consideration of their practical significance.

(a) The external FCIs are found to enhance the forecast accuracy of three out of the four target variables, as shown from forecasting encompassing tests, even though it is possible to build models without these FCIs as roughly equally well-fitted as the models with the FCIs, when judged by in-sample model encompassing tests. The somewhat contrasting result of the two types of encompassing tests can be interpreted as reflecting how much the Chinese economy has become prone to the external financial conditions in spite of the fact that foreign trade has remained the dominant channel of its link to the world economy. This finding not only highlights the need to extend conventionally built macro models by explicitly taking into account of the external financial shocks but also indicates some possible channels of these shocks into the Chinese economy. In particular, the significant predictive power of the FCIs with respect to the import price variable shows us a promising way of improving the forecasts of this variable, which has been treated as exogenous so far, e.g. see Qin *et al* (2007b) and He (2010).

(b) The information content of the FCIs is found to be much richer than that of a single interest rate variable and/or an aggregate money variable, which are used traditionally to represent the financial sector in macroeconomics. This finding strengthens a number of extant results, e.g. Hatzius *et al* (2010). Moreover, it supports the factor-model based approach, as long as forecasting is set as the key criterion for the construction of FCIs. The lack of explanatory power of the OECD FCI or the Bloomberg FCI, in this context, may reflect the problem of weight choice for individual indicators, since the time-varying feature of these weights has been repeatedly observed from the instability of loading coefficients in factor models, e.g. see Stock and Watson (2009). Our modelling experiment also demonstrates the inadequacy of having one single composite FCI. It illustrates, not only with our FCIs but also the FCIs by Hatzius *et al* (2010), that more than one factor is often required to secure the FCIs into the significantly explanatory role and the predictive power enhancing role as well. It therefore supports the view that different financial indices are needed for different purposes, e.g. see Ng (2011). For example, a composite indicator of acute financial stress may not serve the purpose of summarily representing the general financial conditions or shocks well.

(c) The need for multiple FCIs to raise predictive power is shown to be innately related to the rich and varied dynamic information contained in financial indicators when an extensive range of them are considered. By separately extracting long-run FCIs from short-run FCIs and representing their different leading roles by means of the EC-augmented VAR model, our experiment highlights the importance of selecting and designing indicators by their different dynamic properties, as well as the need to take into explicit consideration, during the selection, how to synchronise them with the dynamic properties of the target variables for forecasting. It thus exposes the belief that the explanatory and predictive power of FCIs is bound to increase with the use of higher frequency financial data as conceptually misleading. In other words, the advantage of exploiting higher frequency financial data for forecasting the real-sector economy does not necessarily lie in the shorter-run shocks embodied in the data, such as the case of our monthly FCI as compared to the quarterly FCIs; rather, the advantage may lie mainly in the speedy updating of the dynamic information needed for any leading indicators to be effective. In that respect, separate extraction of the long-run and the short-run FCIs is conceptually superior to the mixed indicator extraction, although FCIs by the latter method may well result in forecasting models of equivalent predictive power to those built with FCIs using the separate extraction method.

As to the way forward, two avenues of extending our present study are easily envisaged. In terms of empirical research, the FCIs constructed here are general enough to be applicable to modelling the impact of aggregate financial shocks external to economies other than China, especially economies of the Pacific and the ASEAN regions. Apart from geographical expansion, a wider choice of the target variables than the four tried at present could also be experimented. In terms of methodological research, further investigation is highly desired to improve the dynamic properties of the constructed FCIs. More attention should be focused on how to improve the intelligence in selecting and grouping indicators through a better combination of structural modelling knowledge with this kind of high-dimension data reduction techniques. In particular, we should aim at searching for a systematic way of reducing the number of indicators to a parsimonious set without significant information loss in the resulting FCIs. But more importantly, we need to refine the designing process of separate indicator sets to ensure that (i) the FCIs extracted from each set maintain an as high as possible degree of stability with respect to changing sample periods, a property, discussed in Stock and Watson (2009) and also in Bate *et al* (2012), which is particularly essential for the forecasting purpose, (ii) the FCIs extracted from each set enjoy relatively easy economic and dynamic interpretability, and (iii) the information content contained jointly in all the FCIs extracted from the separate indicator sets is adequately rich as embodied by their proved role of being significant and robust leading indicators in the forecasting models of concern.

References

Alessi, L. and C. Detken (2009) Real time early warning indicators for costly asset price boom/bust Cycles: A role for global liquidity, *ECB Working Paper*, no 1039.

Banerjee, A., M. Marcellino and I. Masten (2010) Forecasting with factor-augmented error correction models, CPER DP7677.

Bate, B. J., M. Plagborg-Moller, J. H. Stock and M. W. Watson (2012) Consistent factor estimation in dynamic factor models with structural instability, http://www.princeton.edu/~mwatson/wp.html

Borio, C and P Lowe (2004) Securing sustainable price stability. Should credit come back from the wilderness? *BIS Working Papers*, no 157.

Castle, J.L., N.W.P. Fawcett and D.F. Hendry (2011) Forecasting breaks and during breaks, in M.P. Clements and D.F. Hendry eds., Oxford Handbook of Economic Forecasting, University of Oxford Press, pp. 315-54.

Clements, M.P. and D.F. Hendry (2002) Modelling methodology and forecast failure, *The Econometrics Journal*, **5**, 319-44.

Drehmann, M, C. Borio and K. Tsatsaronis (2012) Characterising the financial cycle: don't lose sight of the medium term!, BIS working paper No. 380.

Fidrmuc, J. and I. Korhonen (2010) The impact of the global financial crisis on business cycles in Asian emerging economies, *Journal of Asian Economics*, **21**, 293–303.

Giot, P. and M. Petitjean (2009) Short-term market timing using the bond-equity yield ratio, *European Journal of Finance*, 15, 365-84.

Guichard, S., D. Haugh and D. Turner (2009) Quantifying the effect of the financial conditions in the Euro area, Japan, the United Kingdom and United States, OECD Economics Working Papers, no. 677.

Harvey, D., S.T. Leybourne and P. Newbold (1998) Tests for forecasting encompassing, *Journal of Business and Economic Statistics*, **16**, 254-9.

Hatzius, J, P Hooper, F Mishkin, K Schoenholtz, M Watson (2010): Financial conditions indexes: a fresh look after the financial crisis, *NBER Working Papers*, no 16150 (www.nber.org/papers/w16150).

He, X-H. (2010) MCM_QEM: A Quarterly Multi-Country/Regional Macroeconometric Model, China Financial and Economic Publishing House (in Chinese).

Holló, D., M. Kremer and M.L. Duca (2012) CISS – A composite indicator of systemic stress in the financial system, *ECB Working Paper Series* No. 1426.

Hendry, D.F. (1995) Dynamic Econometrics. Oxford University Press, Oxford.

Hendry, D.F. (2009) The methodology of empirical econometric modelling: Applied econometrics through the looking-glass, in Patterson, K. and Mills, T. C. (eds.) *Palgrave Handbook of Econometrics*, vol. 2. Houndmills: Palgrave MacMillan, pp. 3-67.

Hendry, D.F. (2011) Unpredictability in economic analysis, econometric modelling and forecasting, *Economics Working Papers* 551, University of Oxford.

Hendry, D.F. and M.P. Clements (2004) Pooling of forecasts, *Econometrics Journal*, **7**, 1-31.

Klein, L.R. and R.F. Kosobud (1961) Some econometrics of growth: Great ratios of economics, *Quarterly Journal of Economics*, 75, 173-98.

Luo, Z. and X.-B. Guo (2010) The price effect of imported goods on urban household expenditure, Economic Research Journal, December, 111-24. (in Chinese)

Ng, T. (2011) The predictive content of financial cycle measures for output fluctuations, *BIS Quarterly Review*, June, 53-65.

Onatski, A. (2009) Testing hypotheses about the number of factors in large factor models, *Econometrica*, 77, 1447-79.

Osorio, C., R. Pongsaparn and D.F. Unsal (2011) A quantitative assessment of financial conditions in Asia, IMF working paper WP/11/170.

Park, Y.C. and K.H. Shin (2009) Economic integration and changes in the business cycle in East Asia: Is the region decoupling from the rest of the world? Asian Economic Papers, 8, 107-40.

Qin, D. (1994) Money Demand in China: the Effect of Economic Reform. *Journal of Asian Economics*, **5**, 523-71.

Qin, D. (2008) Uncover latent PPP by dynamic factor error correction model (DF-ECM) approach: Evidence from five OECD countries. *Economics: The Open-Access, Open-Assessment E-Journal* (Special Issue: Recent Developments in International Money and Finance) http://www.economics-ejournal.org/economics/journalarticles/2008-7.

Qin, D., X.-H. He, S.-G. Liu and P. Quising (2005) Modelling Monetary Transmission and Policy in People's Republic of China, *Journal of Policy Modelling*, **27**, 157-75.

Qin, D., Cagas, M.A., Ducanes, G., Magtibay-Ramos, N., Quising, P. (2007a) Measuring regional market integration in developing Asia: A dynamic factor error correction model (DF-ECM) approach. ADB Working Paper Series on Regional Economic Integration no. 08.

Qin, D., Cagas, M.A., Ducanes, G., X-H He, R. Liu, S.-G. Liu, Magtibay-Ramos, N. and Quising, P. (2007b) A Macroeconometric Model of the Chinese Economy, *Economic Modelling*, **24**, 814-22.

Qin, D., Cagas, M.A., Ducanes, G., Magtibay-Ramos, N., Quising, P. (2008) Automatic leading indicators versus macroeconometric structural models: A comparison of inflation and GDP growth forecasting, *International Journal of Forecasting*, **24**, 399-413.

Stock, J.H. and M.W. Watson (2009) Forecasting in Dynamic Factor Models Subject to Structural Instability, in J. Castle and N. Shephard eds. The Methodology and Practice of Econometrics: A Festschrift in Honour of David F. Hendry, Oxford University Press, pp. 173-205.

Xue, Y. and Y. He (2010) The impact of the sub-prime crisis on the Chinese economy, *Journal of Financial Research* (in Chinese), no. 5, 69-83.

Yuan, C.-Q., S.-F. Liu and N.-M. Xie (2010) The impact on Chinese economic growth and energy consumption of the global financial crisis: An input–output analysis, *Energy*, **35**, 1805-12.

Appendix: Variable definitions and data sources

1 Indicators in the long-run data set (see Table 1.1 for the variable definition)

BE_R_UK=R_BRate_UK-R_EquityYield_UK

BE_R_US=R_BRate_US-R_EquityYield_US

CIP_EU= (R_MRate_EU-R_MRate_US)-(ln(1/R_ERF_EU)-ln(R_ER_EU))

CIP_JP= (R_MRate_JP-R_MRate_US)-(ln(R_ERF_JP)-ln(R_ER_JP))

CIP_UK= (R_MRate_UK-R_MRate_US)-(ln(1/R_ERF_UK)-ln(R_ER_UK))

ECPI_R_DE=R_EP_DE/R_CPI_DE

ECPI_R_FR=R_EP_FR/R_CPI_FR

ECPI_R_UK=R_EP_UK/R_CPI_UK

ECPI_R_US=R_EP_US/R_CPI_US

Gov_SP_DE=R_BRate_DE-R_TRate_DE

Gov_SP_JP=R_BRate_JP-R_TRate_JP

Gov_SP_UK=R_BRate_UK-R_TRate_UK

Gov_SP_US=R_BRate_US-R_TRate_US

LD_R_EU= R_Loan_EU/R_Deposit_EU

LD_R_UK= R_Loan_UK/R_Deposit_UK

LD_R_US= R_Loan_US/R_Deposit_US

LOIS_SP_EU=R_LOIS_EU

LOIS_SP_JP=R_LOIS_JP

LOIS_SP_US=R_LOIS_US

MRate_SP_EU=R_MRate_EU-R_Libor_EU

MRate_SP_JP=R_MRate_JP-R_Libor_JP

MRate_SP_UK=R_MRate_UK-R_Libor_UK

RRate_3m_UK=R_MRate_UK-g(R_CPI_UK)

RRate_3m_US=R_MRate_US-g(R_CPI_US)

S&P_R_US= R_S&PF_US/R_S&P_US

S&PTF_R_US= R_S&PTF_US/R_S&PT_US

TED_SP_UK= R_MRate_UK- R_TRate_UK

TED_SP_US= R_MRate_US- R_TRate_US

TSE_R_JP= R_TSEF_JP/R_TSE_JP

2 Indicators in the short-run data set (see Table 1.2 for the variable definition) Δ denotes difference, and g denotes growth rate

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)

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)

ER_JP=g(R_ER_JP)

ER_UK=g(R_ER_UK)

FI_DE=g(R_FI_DE)

FI_JP=g(R_FI_JP)

FI_US=g(R_FI_US)

HP_JP=g((R_HP1_JP+R_HP2_JP+R_HP3_JP+R_HP4_JP)/4)

HP_UK=g(R_HP_UK)

HP_US=g(R_HP_US)

JPMGB=g(R_JPMGB)

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))

MRate_EU=Δ(R_MRate_EU)

MRate_JP=Δ(R_MRate_JP)

MRate_UK=Δ(R_MRate_UK)

MRate_US=Δ(R_MRate_US)

OilPF=g(OilPF)

ORF_EU=g(R_ORF_EU)

ORF_US=g(R_ORF_US)

ORO_JP=g(R_ORO_JP)

3 Variables used for the indicators and data sources

Name	Description	Source	Start	End
R_BRate_DE	German Public Debt Sec Yield: Residual Maturity: >7 Years: 9 to 10 Years	CEIC	1990M1	2012M6
R_BRate_EU	European Central Bank: Government Bond Yield: Monthly Average: Euro: 10 Years %	CEIC	1989M1	2012M6
R_BRate_FR	Bank of France: Government Bond Yield: Monthly Average: 10 Years %	CEIC	1999M1	2012M6
R_BRate_JP	Bank of Japan: Bonds Yield: Government Bonds: To Subscribers: 10 Years: Average %	CEIC	1990M7	2012M5
R_BRate_UK	UK: Office of National Statistics: Government Bond Yield: Zero Coupon: 10 Years %	CEIC	1989M1	2012M1
R_BRate_UK1	Government Bond Yield: Zero Coupon: Monthly Avg: 10 Years: Bank of England	CEIC	1990M1	2012M6
R_BRate_US	US: Federal Reserve Board: State and Local Govt Bonds Yield: 20 Years to Maturity: %	CEIC	1989M1	2012M6
R_ComP	World Bank LMICs (Units: Index Number)	IMF	1991M1	2011M12
R_CPI_DE	DE: Consumer Price Index: 2005=100: IMF	CEIC	1991M1	2012M5
R_CPI_FR	FR: Consumer Price Index: 2005=100: IMF	CEIC	1989M1	2012M4
R_CPI_UK	UK: Consumer Price Index : 2005=100*: IMF*	CEIC	1989M1	2012M5
R_CPI_US	US: Consumer Price Index : 2005=100: IMF	CEIC	1989M1	2012M5
R_Deposit_EU	European Central Bank: MFIs: Liabilities: Agg: Deposits)	CEIC	1997M9	2012M5
R_Deposit_UK	Bank of England: MFIs: Excl CB: Con to MFIs (CM): Lia: Currency, Dep (CD): Pte: GBP	CEIC	1998M4	2012M5
R_Deposit_US	US: Commercial Banks: Deposits: Federal Reserve Board	CEIC	1990M1	2012M5
R_EMF_US	Index: Standard & Poors: Financial: Standard & Poor's		1989M1	2012M6
R_EP_DE	DE: Index: Share Price (End of Period): IMF	CEIC	1989M1	2012M5
R_EP_FR	FR: Index: Share Price: IMF: 2005=100	CEIC	1989M1	2012M4
R_EP_JP	JP: Index: Share Price: IMF: 2005=100	CEIC	1989M1	2012M5
R_EP_UK	UK: Index: Share Price: IMF: 2005=100		1989M1	2012M5
R_EP_US	US: Index: Share Price: IMF: 2005=100		1989M1	2012M5
R_EquityYield_UK	Dividend Yield: MA: Actuaries Share Index: FTSE All Share：%	CEIC	1990M1	2012M6
R_EquityYield_US	Bloomberg: S&P500 earning yield	Bloomberg	1990M1	2007M10
R_ER_EU	CEIC Generate: EUR/USD: Monthly Average	CEIC	1999M1	2012M6
R_ER_JP	Official Rate: End of Period: JPY/USD: IMF	CEIC	1989M1	2012M5
R_ER_UK	Official Rate: End of Period: GBP/USD: IMF	CEIC	1989M1	2012M5
R_ERF_EU	European Central Bank: FX Reference Rate: US Dollar/Euro:	CEIC	1990M1	2012M6
R_ERF_JP	JP: Forward Exchange Rate: 3 Months: IMF: JPY/USD	CEIC	1990M1	2006M9
R_ERF_UK	UK: Forward Exchange Rate: 3 Months: USD/GBP: IMF	CEIC	1989M1	2012M6
R_FI_DE	Futures Bloomberg: Generic 1st GX: last day of each month	Bloomberg	1990M11	2012M6
R_FI_JP	Futures index Bloomberg: Generic 1st NK: last day of each month	Bloomberg	1989M1	2012M6
R_FI_US	Futures Bloomberg: Generic 1st S&P: last day of each month	Bloomberg	1989M1	2012M6
R_HP_JP	'=(R_HP1_JP+R_HP2_JP+R_HP3_JP+R_HP4_JP)/4			
R_HP_UK	UK: House Price: Average: Nationwide	CEIC	1991M1	2012M6

Name	Description	Source	Start	End
R_HP_US	US: House Price Index: FHFA: Purchase Only: Federal Housing Finance Agency	CEIC	1991M1	2012M4
R_HP1_JP	TSE Home Price Index: Used Condominium: Tokyo: Jan2000=100	CEIC	1993M6	2012M4
R_HP2_JP	TSE Home Price Index: Used Condominium: Kanagawa: Jan2000=100	CEIC	1993M6	2012M4
R_HP3_JP	TSE Home Price Index: Used Condominium: Chiba: Jan2000=100	CEIC	1993M6	2012M4
R_HP4_JP	TSE Home Price Index: Used Condominium: Saitama: Jan2000=100	CEIC	1993M6	2012M4
R_JPMGB	JPM global aggregate bond index Market value time 1 million USD: last day of every month	Bloomberg	1989M8	2012M6
R_Libor_EU	EU: Euro Interbank Rate: Month Average: Overnight: Euro Area	CEIC	1994M1	2012M6
R_Libor_JP	JP: Call Rate: Uncollaterized: Overnight: Month Average	CEIC	1990M1	2012M6
R_Libor_UK	UK: Sterling Interbank Rate: Last Fri of the Period: Overnight	CEIC	1990M1	2012M6
R_Loan_EU	European Central Bank: MFIs: Assets: Agg: Loans to Residents	CEIC	1997M9	2012M5
R_Loan_JP	Japan DLB: Assets: LD: Loans	CEIC	1993M10	2012M5
R_Loan_UK	Bank of England: MFIs: Excl CB: CM: Assets: Loans: Private	CEIC	1998M4	2012M5
R_Loan_US	US: Commercial Banks: Credit: Loans and Lease (LL): Federal Reserve Board	CEIC	1989M1	2012M5
R_M1_JP	Japan: Money Supply: M1 ：IMF	CEIC	1989M1	2012M2
R_M1_UK	UK: Money Supply: M1: IMF	CEIC	1989M1	2012M5
R_M1_US	US: Money Supply: M1: IMF	CEIC	1989M1	2012M5
R_MRate_EU	EU: European Central Bank: Euro Interbank Rate: Month Average: 3 Months: Euro Area	CEIC	1994M1	2012M6
R_MRate_JP	Japan: Bank of Japan: Call Rate: Uncollaterized: 3 Months: Month Average	CEIC	1989M1	2012M6
R_MRate_UK	UK: Office of National Statistics: Sterling Interbank Rate: Last Fri of the Period: 3 Months	CEIC	1989M1	2012M2
R_MRate_US	US Dollar 3-month British Bankers` Association (BBA) Libor, Historical close, average of observations through period	ECB website	1990M1	2012M6
R_OilPF	Oil price futures	Bloomberg	1990.M1	2012M6
R_ORF_EU	Open Interest: Total Futures	CEIC	2002M1	2012M6
R_ORF_US	Open Interest: CBOT: Futures: Financial	CEIC	1989M1	2012M6
R_ORO_JP	OSE: Open Interest: Nikkei 225 Options	CEIC	1989M6	2012M5
R_S&P_US	US: Index: Standard & Poors 500	CEIC	1990M1	2012M6
R_S&PF_US	US: Index: Standard & Poors: Financial	CEIC	1990M1	2012M6
R_S&PT_US	US: Index: Standard & Poors: S&P Global 100	CEIC	2001M12	2012M5
R_S&PTF_US	US: Index: Standard & Poors: S&P Global 1200 Financials	CEIC	2001M12	2012M5
R_TRate_DE	German Public Debt Sec Yield: Residual Maturity: 1 to 2 Years	CEIC	1990M1	2012M6
R_TRate_JP	JP: Treasury Bill Rate: Government Securities: IMF	IMF	1990M1	2012M5
R_TRate_UK	UK: Treasury Bill Rate: Government Securities: IMF	IMF	1990M1	2012M5
R_TRate_US	US: Short Term Interest Rate: Month End: Treasury Bills: 3 Months: CEIC Generate	CEIC	1990M1	2012M6
R_TSE_JP	Japan: Index: TSE 1st Section Composite	CEIC	1994M1	2012M6
R_TSEF_JP	Japan: Index: TSE: 1st Section: Banks	CEIC	1990M1	2012M6

4 Variables used as explained variable from China Economic Information Network

y_1: Monthly import price index of China, y-o-y, 1993M1-2012M6.

y_2: Monthly 61 to 90 days interbank interest rate of China, annual percentage, 1996M1-2012M6.

y_3: China monthly export in thousand of US dollars, 1990M1-2012M6.

y_4: Monthly money supply of China, M1, in 100 million RMB yuan, 1990M1-2012M6.

Tables and figures

Table 1.1 Indicators of the long-run set

Cross-variable transformations	Japan	US	UK	euro area or France and/or Germany
Overnight/3-month spread	MRate_SP_JP		MRate_SP_UK	MRate_SP_EU
3-month market/3-month T-bill spread		TED_SP_US	TED_SP_UK	
3-month T-bill/10-year or longer T-bond spread	Gov_SP_JP	Gov_SP_US	Gov_SP_UK	Gov_SP_DE
LIBOR/OIS spread	LOIS_SP_JP	LOIS_SP_US		LOIS_SP_EU
Bond-equity yield ratio		BE_R_US	BE_R_UK	
3-month market rate net of inflation rate		RRate_3m_US	RRate_3m_UK	
3-month covered interest rate parity vis-à-vis US$	CIP_JP		CIP_UK	CIP_EU
Equity price index/CPI ratio		ECPI_R_US	ECPI_R_UK	ECPI_R_FR ECPI_R_DE
Financial sector equity price index/Equity price index ratio	TSE_R_JP	S&PTF_R_US S&P_R_US*		
Bank lending/deposit ratio		LD_R_US	LD_R_UK	LD_R_EU

* S&P_R_US is the ratio of the S&P500 financial sector index to S&P500 index, while S&PTF_R_US is the ratio of the S&P global financial 1200 index to S&P global 100 index.

Table 1.2 Indicators of the short-run set

Variables (in growth rate or difference)	Japan	US	UK	euro area	World
3-month parallel market rate	MRate_JP		MRate_UK	MRate_EU	
10-year or longer T-bond yield	BRate_JP	BRate_US	BRate_UK	BRate_EU BRate_DE BRate_FR	
Exchange rate vis-à-vis US$	ER_JP		ER_UK		
Equity market price index	EP_JP	EP_US	EP_UK		
Equity market financial-sector index		EMF_US			
Futures market index	FI_JP	FI_US		FI_DE	
Open interest of futures market		ORF_US		ORF_EU	
Open interest of options market	ORO_JP				
M1 (CPI deflated)	M1_JP	M1_US	M1_UK		
Bank lending (CPI deflated)	Loan_JP	Loan_US	Loan_UK		
House price index	HP_JP	HP_US	HP_UK		
Commodities price index					ComP
Oil price futures					OilPF
Aggregate bond index market value					JPMGB

Note: Three short-run sets are produced by taking monthly, quarterly and annual spans respectively for differencing.

Table 2 Specification of the DFM (1)

	f_t^l	$f_t^{s_1}$	$f_t^{s_2}$	$f_t^{s_3}$	$f_t^{m_1}$	$f_t^{m_2}$	$f_t^{m_3}$
m: number of factors determined by the Onatski procedure	3	1	1	1	1	3	3
L: lag length of DFMs	2	2	3	1	2	1	1

Table 3 Key results of the parsimonious models (3a), (3b) and (4) (end of sample point: 2010M12)

Import price index:

(3a)
$$\Delta y_{1t} = \underset{\substack{(3.18)\\(0.059)}}{19.84} + \underset{\substack{(0.067)\\(0.369)}}{0.270}\,\Delta y_{1,t-3} + \underset{\substack{(0.837)\\(0.090)}}{1.623}\,\Delta_3 f^{m_2}_{2,t-1} - \underset{\substack{(0.642)\\(0.108)}}{1.324}\,\Delta f^{m_2}_{3,t-1} - \underset{\substack{(0.031)\\(0.057}}{0.194}\left(y_1 - 4 f_2^{m_2} + 4 f_3^{m_2} + 4 f_1^{m_3}\right)_{t-1} + \underset{\substack{(2.955)\\(0.123)}}{\hat{e}_{1t}}$$

(3b)
$$\Delta y_{1t} = \underset{\substack{(3.49)\\(0.094)}}{20.82} + \underset{\substack{(0.069)\\(0.236)}}{0.222}\,\Delta y_{1t-3} - \underset{\substack{(0.283)\\(0.187)}}{0.667}\, f^{s_1}_{t-1} - \underset{\substack{(0.109)\\(0.201)}}{0.501}\, f^{s_3}_{t-1} + \underset{\substack{(0.965)\\(0.142)}}{2.942}\,\Delta f^{l}_{1,t-1} - \underset{\substack{(0.034)\\(0.111)}}{0.203}\left(y_1 + 1.4 f_2^{l}\right)_{t-1} + \underset{\substack{(2.976)\\(0.058)}}{\hat{e}_{1t}}$$

(4)
$$\Delta y_{1t} = +\underset{\substack{(0.073)\\(0.426)}}{0.191}\,\Delta y_{1t-3} + \underset{\substack{(13.65)\\(0.098)}}{50.189}\,\Delta\ln(y_4)_{t-3} - \underset{\substack{(13.65)\\(0.060)}}{49.366}\,\Delta\ln(y_4)_{t-4} + \underset{\substack{(3.171)\\(0.312)}}{\hat{e}_{1t}}$$

Interbank rate:

(3a)
$$\Delta y_{2t} = \underset{\substack{(0.146)\\(0.137)}}{0.521} - \underset{\substack{(0.069)\\(0.146)}}{0.599}\,\Delta y_{2t-1} - \underset{\substack{(0.069)\\(0.048)}}{0.336}\,\Delta y_{2t-2} - \underset{\substack{(0.272)\\(0.317)}}{0.746}\,\Delta f^{m_1}_{t-1} - \underset{\substack{(0.069)\\(0.221)}}{0.172}\,\Delta_2 f^{m_3}_{2t-1} - \underset{\substack{(0.021)\\(0.066)}}{0.099}\left(y_2 + 2 f^{m_1} + 2 f_2^{m_2}\right)_{t-1} + \underset{\substack{(0.872)\\(0.96)*}}{\hat{e}_{2t}}$$

(3b)
$$\Delta y_{2t} = \underset{\substack{(0.143)\\(0.053)}}{0.455} - \underset{\substack{(0.068)\\(0.154)}}{0.586}\,\Delta y_{2t-1} - \underset{\substack{(0.067)\\(0.051)}}{0.339}\,\Delta y_{2t-2} - \underset{\substack{(0.061)\\(0.084)}}{0.169}\, f^{s_1}_{t-2} + \underset{\substack{(0.109)\\(0.418)}}{0.282}\,\Delta f^{s_3}_{t-2} - \underset{\substack{(0.31)\\(0.077)}}{1.287}\,\Delta f^{l}_{2,t-1} + \underset{\substack{(0.183)\\(0.025)}}{0.684}\,\Delta f^{l}_{3,t-1} - \underset{\substack{(0.028)\\(0.021)}}{0.139}\left(y_2 + 0.5 f_2^{l} + 0.5 f_3^{l}\right)_{t-1} + \underset{\substack{(0.847)\\(1.133)*}}{\hat{e}_{2t}}$$

(4)
$$\Delta y_{2t} = -\underset{\substack{(0.072)\\(0.139)}}{0.606}\,\Delta y_{2t-1} - \underset{\substack{(0.071)\\(0.062)}}{0.320}\,\Delta y_{2t-2} + \underset{\substack{(3.770)\\(0.758)*}}{8.955}\,\Delta\ln(y_4)_{t-2} - \underset{\substack{(3.774)\\(0.771)*}}{9.421}\,\Delta\ln(y_4)_{t-3} + \underset{\substack{(0.020)\\(0.035)}}{0.041}\,\Delta(y_1)_{t-3} + \underset{\substack{(0.911)\\(1.004)*}}{\hat{e}_{2t}}$$

Exports:

(3a)
$$\Delta\ln(y_{3t}) = \underset{\substack{(0.155)\\(0.045)}}{1.443} + \underset{\substack{(0.064)\\(0.099)}}{0.154}\,\Delta\ln(y_3)_{t-2} + \underset{\substack{(0.001)\\(0.100)}}{0.002}\,\Delta_6 y_{1t-1} - \underset{\substack{(0.015)\\(0.043)}}{0.066}\, f^{m_1}_{t-3} + \underset{\substack{(0.012)\\(0.026)}}{0.038}\,\Delta f^{m_2}_{1t-3} + \underset{\substack{(0.020)\\(0.063)}}{0.145}\, f^{m_2}_{2t-1} + \underset{\substack{(0.010)\\(0.054)}}{0.021}\, f^{m_2}_{2t-2} - \underset{\substack{(0.014)\\(0.063)}}{0.115}\, f^{m_2}_{3t-1} - \underset{\substack{(0.018)\\(0.045)}}{0.172}\, f^{m_3}_{1t-1}$$
$$- \underset{\substack{(0.008)\\(0.034)}}{0.048}\, f^{m_3}_{2t-1} + \underset{\substack{(0.010)\\(0.183)}}{0.052}\,\Delta_3 f^{m_3}_{3t-1} - \underset{\substack{(0.025)\\(0.046)}}{0.219}\left(\ln\left(\frac{y_3}{y_4}\right) - 0.25 f_1^{m_1} - 0.15 f_2^{m_2} - 0.03 f_2^{m_3}\right)_{t-1} + \underset{\substack{(0.065)\\(0.314)}}{\hat{e}_{3t}}$$

(3b)
$$\Delta\ln(y_{3t}) = \underset{\substack{(0.063)\\(0.172)}}{0.361}\,\Delta\ln(y_3)_{t-1} + \underset{\substack{(0.061)\\(0.222)}}{0.443}\,\Delta\ln(y_3)_{t-2} + \underset{\substack{(0.001)\\(0.068)}}{0.002}\,\Delta_6 y_{1t-1} - \underset{\substack{(0.003)\\(0.259)}}{0.011}\, f^{s_2}_{t-3} - \underset{\substack{(0.024)\\(0.039)}}{0.1}\,\Delta f^{l}_{2t-1} - \underset{\substack{(0.014)\\(0.015)}}{0.043}\,\Delta\Delta f^{l}_{3t-1}$$
$$- \underset{\substack{(0.021)\\(0.123)}}{0.088}\left(\ln\left(\frac{y_3}{y_4}\right) + 0.08 f_2^{l} - 6.5\right)_{t-1} + \underset{\substack{(0.072)\\(0.297)}}{\hat{e}_{3t}}$$

(4)
$$\Delta\ln(y_{3t}) = \underset{\substack{(0.078)\\(0.072)}}{0.273}\,\Delta\ln(y_3)_{t-1} + \underset{\substack{(0.076)\\(0.113)}}{0.347}\,\Delta\ln(y_3)_{t-2} + \underset{\substack{(0.076)\\(0.120)}}{0.246}\,\Delta\ln(y_3)_{t-3} + \underset{\substack{(0.054)\\(0.083)}}{0.143}\,\Delta\ln(y_4)_{t-1} + \underset{\substack{(0.002)\\(0.268)}}{0.005}\,\Delta y_{1t-1} + \underset{\substack{(0.002)\\(0.332)}}{0.008}\,\Delta y_{1t-2} + \underset{\substack{(0.005)\\(0.117)}}{0.005}\,\Delta y_{1t-3} + \underset{\substack{(0.077)\\(0.467)}}{\hat{e}_{3t}}$$

M1:

(3a)
$$\Delta\ln(y_{4t}) = \underset{\substack{(0.031)\\(0.051)}}{0.076} + \underset{\substack{(0.072)\\(0.052)}}{0.684}\,\Delta\ln(y_4)_{t-1} + \underset{\substack{(0.071)\\(0.056)}}{0.223}\,\Delta\ln(y_4)_{t-2} - \underset{\substack{(0.002)\\(0.056)}}{0.01}\, f^{m_2}_{2t-3} + \underset{\substack{(0.001)\\(0.120)}}{0.006}\, f^{m_2}_{3t-3} - \underset{\substack{(0.002)\\(0.133)}}{0.005}\, f^{m_3}_{1t-1} + \underset{\substack{(0.002)\\(0.1)}}{0.013}\, f^{m_3}_{1t-3} - \underset{\substack{(0.001)\\(0.037)}}{0.002}\, f^{m_3}_{3t-2}$$
$$- \underset{\substack{(0.005)\\(0.056)}}{0.015}\left(\ln(y_4) - \ln(y_3) + 0.1 f_3^{m_2}\right)_{t-1} + \underset{\substack{(0.016)\\(0.483)*}}{\hat{e}_{4t}}$$

(3b)
$$\Delta\ln(y_{4t}) = \underset{\substack{(0.012)\\(0.121)}}{0.051} + \underset{\substack{(0.033)\\(0.098)}}{0.847}\,\Delta\ln(y_4)_{t-1} + \underset{\substack{(0.001)\\(0.025)}}{0.002}\,\Delta f^{s_2}_{t-2} - \underset{\substack{(0.001)\\(0.128)}}{0.003}\,\Delta_3 f^{s_3}_{t-1} - \underset{\substack{(0.005)\\(0.043)}}{0.012}\,\Delta f^{l}_{2t-3} - \underset{\substack{(0.014)\\(0.085)}}{0.043}\left(\ln(y_4) - 0.6\ln(y_3) + 0.1 f_2^{l}\right)_{t-1} + \underset{\substack{(0.017)\\(0.320)}}{\hat{e}_{4t}}$$

(4)
$$\Delta\ln(y_{4t}) = \underset{\substack{(0.073)\\(0.168)}}{0.016} + \underset{\substack{(0.000)\\(0.173)}}{0.818}\,\Delta\ln(y_4)_{t-1} + \underset{\substack{(0.088)\\(0.146)}}{0.286}\,\Delta\ln(y_4)_{t-2} - \underset{\substack{(0.058)\\(0.140)}}{0.180}\,\Delta\ln(y_4)_{t-4} - \underset{\substack{(0.009)\\(0.253)}}{0.026}\,\Delta\ln(y_3)_{t-1} + \underset{\substack{(0.017)\\(0.620)*}}{\hat{e}_{4t}}$$

Note: Statistics in the upper parentheses are standard deviations and those in the lower parentheses are the Hansen instability test statistics with those whole *p*-value falls below 5% marked by *. Annual growth rate is used for both exports and M1 equations.

Table 4 Model in-sample encompassing tests

	H_0	Cox test	Sargan test
y_1	(3a) vs (4)	N(0,1) = -4.204 [0.0000]**	$\chi^2(2)$ = 9.9592 [0.0069]**
	(4) vs (3a)	N(0,1) = -19.31 [0.0000]**	χ^2 (4) = 31.832 [0.0000]**
	(3a) vs (3b)	N(0,1) = -2.525 [0.0116]*	χ^2 (4) = 6.5088 [0.1642]
	(3b) vs (3a)	N(0,1) = -1.652 [0.0986]	χ^2 (3) = 2.9934 [0.3926]
	(3b) vs (4)	N(0,1) = -4.429 [0.0000]**	χ^2 (2) = 7.5048 [0.0235]*
	(4) vs (3b)	N(0,1) = -20.36 [0.0000]**	χ^2 (5) = 33.210 [0.0000]**
y_2	(3a) vs (4)	N(0,1) = -4.154 [0.0000]**	χ^2 (3) = 7.4913 [0.0578]
	(4) vs (3a)	N(0,1) = -17.81 [0.0000]**	χ^2 (4) = 20.664 [0.0004]**
	(3a) vs (3b)	N(0,1) = -4.698 [0.0000]**	χ^2 (5) = 17.164 [0.0042]**
	(3b) vs (3a)	N(0,1) = -2.690 [0.0071]**	χ^2 (3) = 5.8535 [0.1190]
	(3b) vs (4)	N(0,1) = -3.283 [0.0010]**	χ^2 (3) = 8.4459 [0.0376]*
	(4) vs (3b)	N(0,1) = -22.93 [0.0000]**	χ^2 (6) = 31.879 [0.0000]**
y_3	(3a) vs (4)	N(0,1) = -1.326 [0.1847]	χ^2 (6) = 3.5553 [0.7366]
	(4) vs (3a)	N(0,1) = -12.80 [0.0000]**	χ^2 (11)= 52.926 [0.0000]**
	(3a) vs (3b)	N(0,1) = -4.279 [0.0000]**	χ^2 (5) = 16.583 [0.0054]**
	(3b) vs (3a)	N(0,1) = -10.81 [0.0000]**	χ^2 (10)= 49.764 [0.0000]**
	(3b) vs (4)	N(0,1) = -2.612 [0.0090]**	χ^2 (5) = 10.811 [0.0552]
	(4) vs (3b)	N(0,1) = -10.03 [0.0000]**	χ^2 (5) = 32.871 [0.0000]**
y_4	(3a) vs (4)	N(0,1) = -1.711 [0.0870]	χ^2 (2) = 2.2517 [0.3244]
	(4) vs (3a)	N(0,1) = -5.967 [0.0000]**	χ^2 (6) = 16.511 [0.0113]*
	(3a) vs (3b)	N(0,1) = -2.304 [0.0212]*	χ^2 (4) = 10.242 [0.0365]*
	(3b) vs (3a)	N(0,1) = -9.831 [0.0000]**	χ^2 (7) = 25.875 [0.0005]**
	(3b) vs (4)	N(0,1) = -11.78 [0.0000]**	χ^2 (3) = 17.956 [0.0004]**
	(4) vs (3b)	N(0,1) = -7.682 [0.0000]**	χ^2 (4) = 16.202 [0.0028]**

Note: Statistics in square bracket are *p*-values, with those smaller than 0.05 marked by * and those smaller than 0.01 marked by **.

Table 5 Key results of the parsimonious models using FCIs by Hatzius et al (2010) (PC3 denote the FCIs from the 3-factor model; monthly series are interpolated from quarterly FCIs; sample ends 2009M12)

y_1 :	$\Delta y_{1t} = \underset{\substack{(3.082)\\(0.107)}}{12.82} + \underset{\substack{(0.076)\\(0.709)^*}}{0.286}\,\Delta y_{1t-3} - \underset{\substack{(0.029)\\(0.109)}}{0.122}\left(y_1 - 3PC3_1\right)_{t-1} + \underset{\substack{(3.216)\\(0.524)^*}}{\hat{e}_{1t}}$
y_2 :	$\Delta y_{2t} = \underset{\substack{(0.133)\\(0.047)}}{0.152} - \underset{\substack{(0.073)\\(0.212)}}{0.617}\,\Delta y_{2t-1} - \underset{\substack{(0.072)\\(0.087)}}{0.333}\,\Delta y_{2t-2} - \underset{\substack{(0.023)\\(0.067)}}{0.058}\,y_{2,t-1} + \underset{\substack{(0.325)\\(0.551)^*}}{0.642}\,\Delta\Delta PC3_{1,t-2} + \underset{\substack{(0.911)\\(0.814)^*}}{\hat{e}_{2t}}$
y_3 :	$\Delta\ln\left(y_{3t}\right) = \underset{\substack{(0.157)\\(1.105)^*}}{0.834} + \underset{\substack{(0.064)\\(0.514)^*}}{0.404}\,\Delta\ln\left(y_3\right)_{t-1} + \underset{\substack{(0.062)\\(0.649)^*}}{0.39}\,\Delta\ln\left(y_3\right)_{t-2} + \underset{\substack{(0.006)\\(0.153)}}{0.016}\,PC3_{1,t-3} + \underset{\substack{(0.039)\\(0.108)}}{0.132}\,\Delta PC3_{2,t-3}$ $- \underset{\substack{(0.025)\\(1.203)^*}}{0.128}\left(\ln\left(y_3\right) - \ln\left(y_4\right)\right)_{t-1} + \underset{\substack{(0.085)\\(0.513)^*}}{\hat{e}_{3t}}$
y_4 :	$\Delta\ln\left(y_{4t}\right) = \underset{\substack{(0.006)\\(0.129)}}{0.014} + \underset{\substack{(0.035)\\(0.227)}}{0.917}\,\Delta\ln\left(y_4\right)_{t-1} + \underset{\substack{(0.005)\\(0.505)^*}}{0.011}\,\Delta PC3_{1,t-2} + \underset{\substack{(0.018)\\(0.96)^*}}{\hat{e}_{4t}}$

Note: Statistics in the upper parentheses are standard deviations and those in the lower parentheses are the Hansen instability test statistics with those whole *p*-value falls below 5% marked by *.
Annual growth rate is used for both exports and M1 equations.

Table 6 Single-equation forecasting test

	Model	Chow test	Zero forecast mean *t*-test
y_1	(4)	F(18,165)= 0.47403 [0.9659]	t(17) = -0.2742 [0.7872]
	(3a)	F(18,170)= 0.47335 [0.9663]	t(17) = -0.02803 [0.9780]
	(3b)	F(18,172)= 0.58522 [0.9069]	t(17) = -1.680 [0.1113]
y_2	(4)	F(18,170)= 0.61665 [0.8834]	t(17) = 1.141 [0.2695]
	(3a)	F(18,171)= 0.69026 [0.8178]	t(17) = 0.7312 [0.4746]
	(3b)	F(18,169)= 0.61727 [0.8829]	t(17) = 1.426 [0.1719]
y_3	(4)	F(18,161)= 1.0678 [0.3892]	t(17) = 0.3854 [0.7047]
	(3a)	F(18,163)= 1.6064 [0.0637]	t(17) = 0.4765 [0.6398]
	(3b)	F(18,168)= 1.8846 [0.0201]*	t(17) = -2.014 [0.0601]
y_4	(4)	F(18,163)= 1.6775 [0.0480]*	t(17) = -2.541 [0.0211]*
	(3a)	F(18,163)= 2.0289 [0.0108]*	t(17) = -3.734 [0.0017]**
	(3b)	F(18,166)= 2.3495 [0.0025]**	t(17) = -4.438 [0.0004]**

Note: Statistics in square bracket are *p*-values, with those smaller than 0.05 marked by * and those smaller than 0.01 marked by **.

Table 7 Forecast encompassing tests against benchmark model (4)

		1 step	2 step	3step	4 step	5 step	6 step
H0: $e^2 < e_B^2$ H1: $e^2 \geq e_B^2$							
y_1	(3a) & Scenario1	-0.794 [0.780]	-0.386 [0.647]	-1.045 [0.843]	-1.468 [0.916]	-1.536 [0.924]	-1.339 [0.895]
	(3a) & Scenario 2	-0.794 [0.780]	-0.101 [0.540]	-0.596 [0.719]	-0.719 [0.757]	-0.600 [0.720]	-0.576 [0.711]
	(3a) & Scenario 3	-0.794 [0.780]	-0.275 [0.606]	-1.105 [0.855]	-1.331 [0.896]	-1.294 [0.889]	-1.128 [0.857]
	(3b) & Scenario 1	0.623 [0.271]	0.845 [0.206]	0.631 [0.270]	0.233 [0.410]	-0.545 [0.702]	-1.025 [0.835]
	(3b) & Scenario 2	0.623 [0.271]	1.200 [0.125]	1.021 [0.163]	0.635 [0.269]	0.112 [0.457]	-0.397 [0.650]
	(3b) & Scenario 3	0.623 [0.271]	1.170 [0.131]	1.192 [0.127]	0.847 [0.207]	0.478 [0.321]	0.065 [0.475]
y_2	(3a) & Scenario 1	0.165 [0.435]	-0.330 [0.627]	0.461 [0.326]	-0.944 [0.818]	-1.011 [0.833]	-0.882 [0.801]
	(3a) & Scenario 2	0.165 [0.435]	-0.009 [0.503]	0.258 [0.400]	-0.502 [0.688]	-0.760 [0.768]	-0.850 [0.792]
	(3a) & Scenario 3	0.165 [0.435]	-0.699 [0.752]	-0.201 [0.578]	-0.766 [0.771]	-0.739 [0.762]	-0.851 [0.793]
	(3b) & Scenario 1	-0.623 [0.729]	-0.588 [0.717]	0.348 [0.367]	-0.158 [0.561]	-0.384 [0.646]	-0.358 [0.636]
	(3b) & Scenario 2	-0.623 [0.729]	1.429 [0.088]	2.360 [0.017]*	1.338 [0.103]	1.151 [0.137]	1.120 [0.144]
	(3b) & Scenario 3	-0.623 [0.729]	-0.016 [0.506]	0.347 [0.367]	-0.159 [0.562]	-0.365 [0.639]	-0.253 [0.597]
y_3	(3a) & Scenario 1	1.506 [0.076]	1.438 [0.085]	0.618 [0.273]	0.523 [0.305]	0.467 [0.324]	0.433 [0.337]
	(3a) & Scenario 2	1.506 [0.076]	1.842 [0.043]*	3.695 [0.001]**	3.381 [0.002]**	2.878 [0.007]**	2.879 [0.008]**
	(3a) & Scenario 3	1.506 [0.076]	1.372 [0.095]	0.475 [0.321]	0.326 [0.375]	0.733 [0.239]	0.887 [0.197]
	(3b) & Scenario 1	1.806 [0.046]*	1.774 [0.048]*	1.558 [0.072]	1.601 [0.068]	1.483 [0.082]	1.388 [0.098]
	(3b) & Scenario 2	1.806 [0.046]*	1.315 [0.104]	1.362 [0.098]	1.674 [0.059]	2.055 [0.031]*	2.484 [0.015]*
	(3b) & Scenario 3	1.806 [0.046]*	1.626 [0.063]	1.699 [0.057]	1.959 [0.037]*	2.304 [0.020]*	2.761 [0.009]**
y_4	(3a) & Scenario 1	2.502 [0.012]	2.538 [0.012]	2.555 [0.012]	2.391 [0.017]	2.114 [0.029]	1.885 [0.044]
	(3a) & Scenario 2	2.502 [0.012]*	2.803 [0.007] **	3.073 [0.004]**	3.214 [0.004] **	3.189 [0.004]**	3.182 [0.005]**
	(3a) & Scenario 3	2.502 [0.012]**	2.673 [0.009]**	2.862 [0.007]**	2.933 [0.006]**	2.962 [0.006]**	3.082 [0.006] **
	(3b) & Scenario 1	3.947 [0.001]**	5.094 [0.000]**	6.145 [0.000]**	7.389 [0.000]**	7.924 [0.000]**	8.336 [0.000]**
	(3b) & Scenario 2	3.947 [0.001]**	5.162 [0.000]**	6.179 [0.000]**	6.849 [0.000]**	6.308 [0.000]**	5.653 [0.000]**
	(3b) & Scenario 3	3.947 [0.001] **	5.101 [0.000] **	5.908 [0.000]**	7.096 [0.000]**	7.338 [0.000]**	6.486 [0.000]**

Note: e^2 is the squared model forecast error and e_B^2 is the squared benchmark model forecast error. Statistics in square bracket are *p*-values with those smaller than 0.05 marked by * and those smaller than 0.01 marked by **.

Table 8.1 RMSFEs of the pooled forecasts as percentage deviations from the RMSFEs of the benchmark model: $\left(\frac{\text{RMSFEs of Pooled Forecasts}}{\text{RMSFE of Benchmark}} - 1\right) \times 100$

	1 step	2 step	3 step	4 step	5 step	6 step
y_1	-3.69	-1.34	-15.5	-32.4	-39.12	-43.79
y_2	-5.34	-4.08	0.74	-7.03	-12.54	-12.89
y_3	14.26	18.52	-18.92	-13.42	-1.81	-7.32
y_4	41.64	78.54	90.16	79.47	73.44	71.92

Table 8.2 *t*-value of the error mean of the pooled forecasts

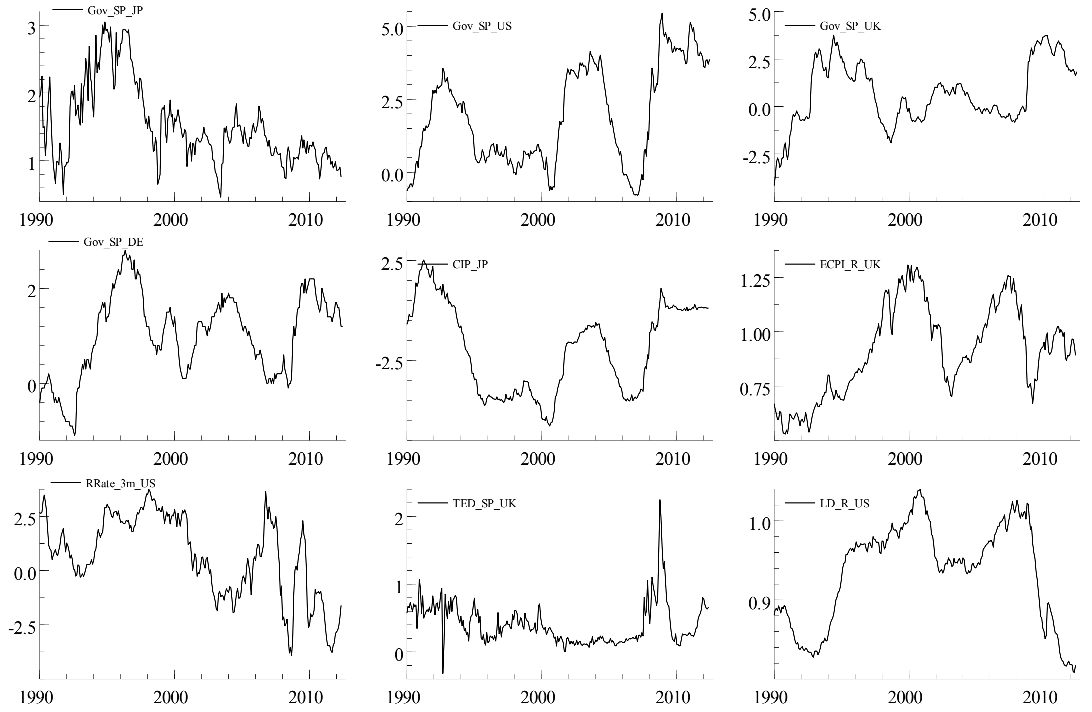
	1 step	2 step	3 step	4 step	5 step	6 step
y_1	0.30	0.39	0.60	0.66	0.57	0.66
y_2	-0.36	-0.41	-0.55	-0.91	-1.15	-1.25
y_3	0.20	0.29	0.39	0.48	0.50	0.57
y_4	1.37	2.20	2.97	3.61	3.77	4.16

Table 8.3 *t-value* of the error mean of the benchmark model's forecasts

	1 step	2 step	3 step	4 step	5 step	6 step
y_1	0.09	0.19	0.33	0.59	0.62	0.74
y_2	-0.38	-0.39	-0.38	-0.54	-0.57	-0.57
y_3	-0.07	0.02	-0.09	0.12	0.32	0.59
y_4	0.56	0.86	1.26	1.48	1.66	2.03

Figure 1.1 Examples of long run indicators

Time Series:



Periodogram:

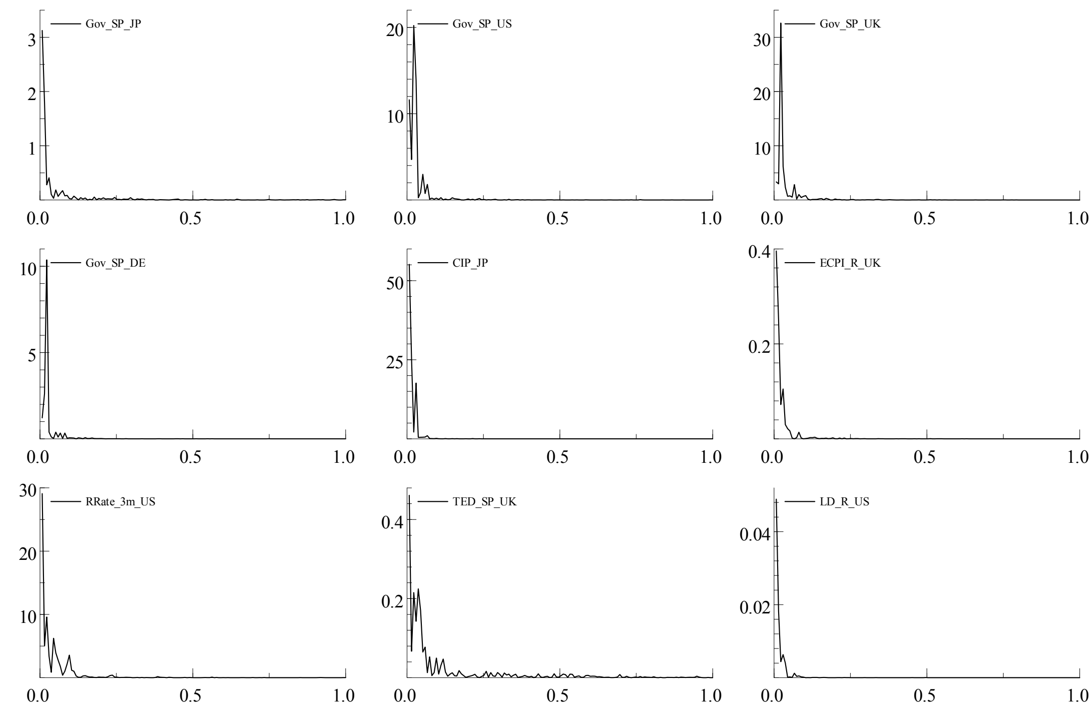
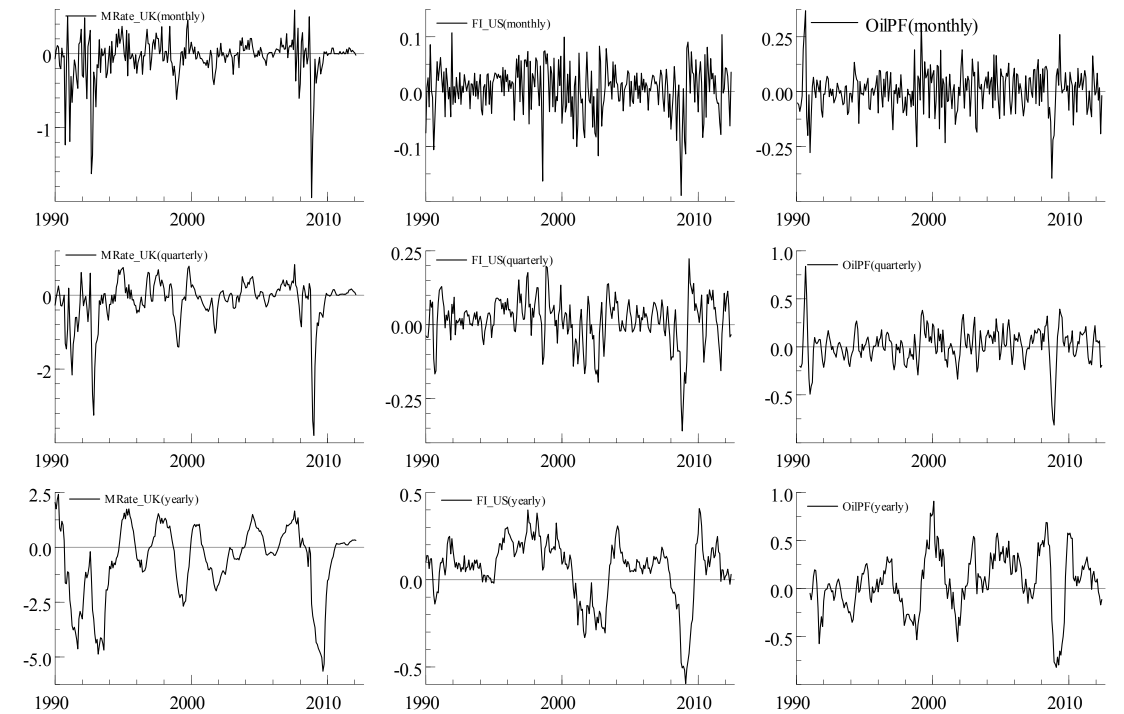


Figure 1.2 Examples of short run indicators

Time Series:



Periodogram:

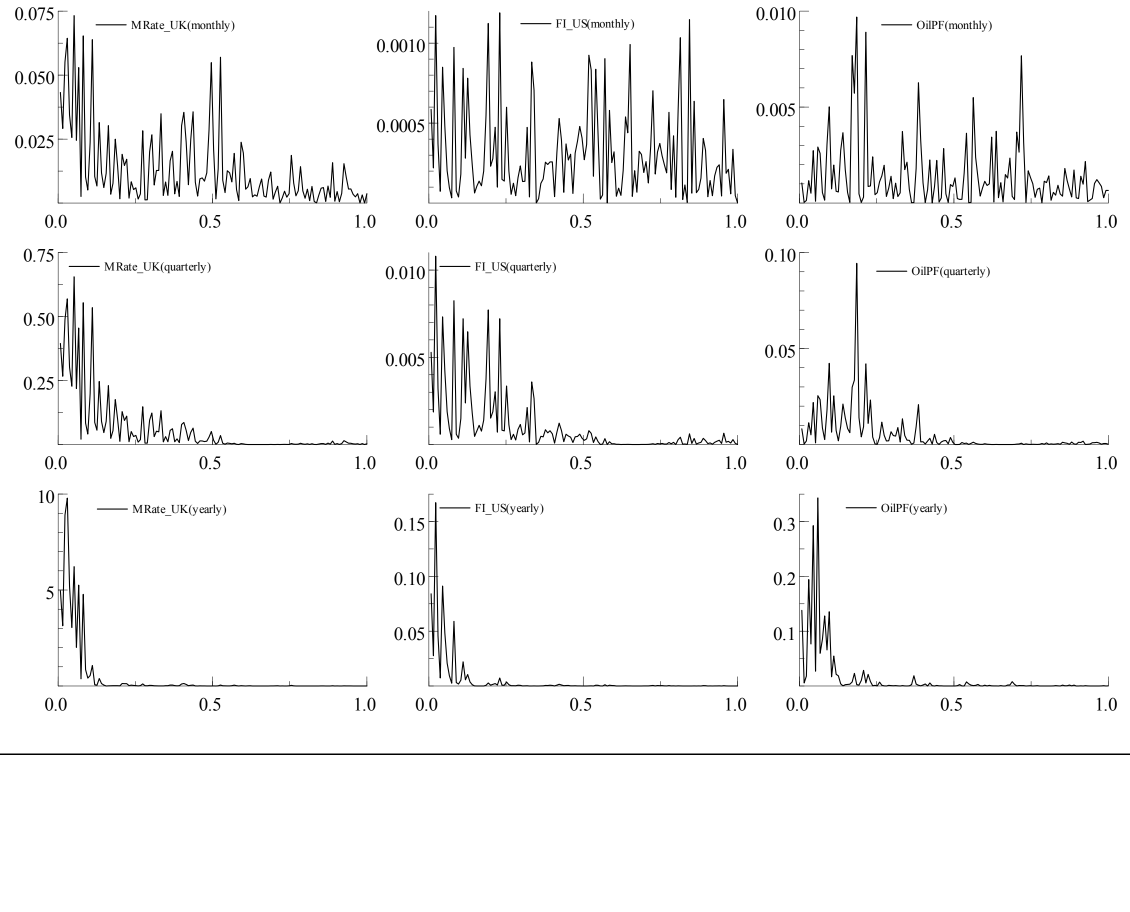


Figure 2.1 Factors and their periodograms: The separate case

Legion notations:

LRF1= f^l_{1t}, LRF2= f^l_{2t}, LRF3= f^l_{3t}; SRFM= $f^{s_1}_t$, SRFQ= $f^{s_2}_t$, SRFY= $f^{s_3}_t$

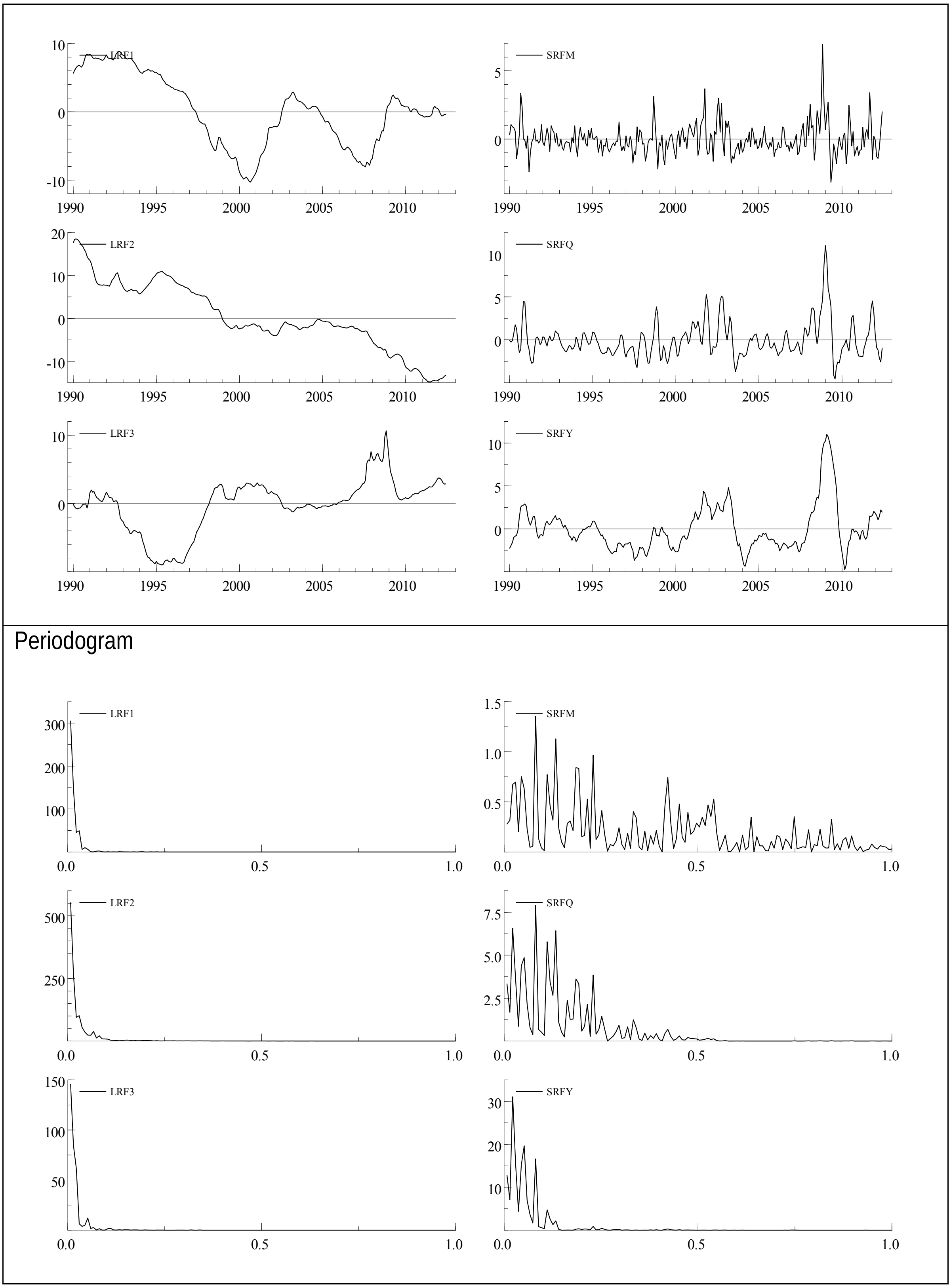
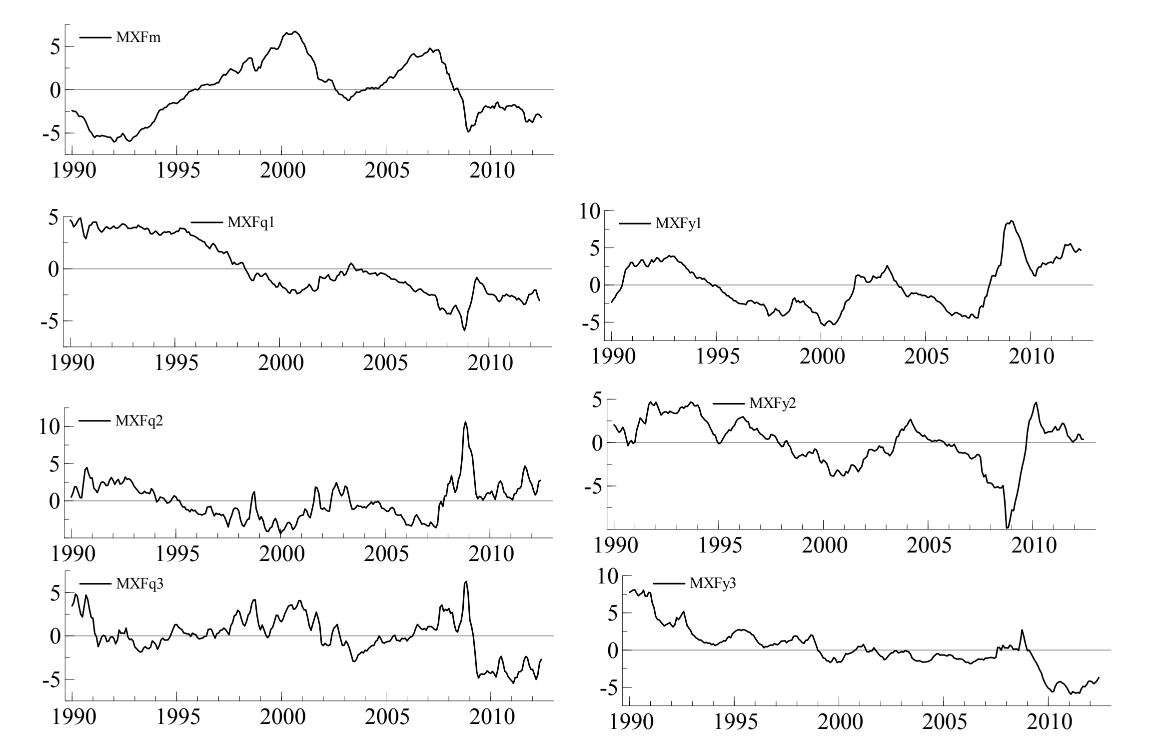


Figure 2.2 Factors and their periodograms: The mixed case

Legion notations:

MXFm= $f_t^{m_1}$, MXFq1= $f_{1t}^{m_2}$, MXFq2= $f_{2t}^{m_2}$, MXFq3= $f_{3t}^{m_2}$; MXFy*i*= $f_{it}^{m_3}$



Periodogram

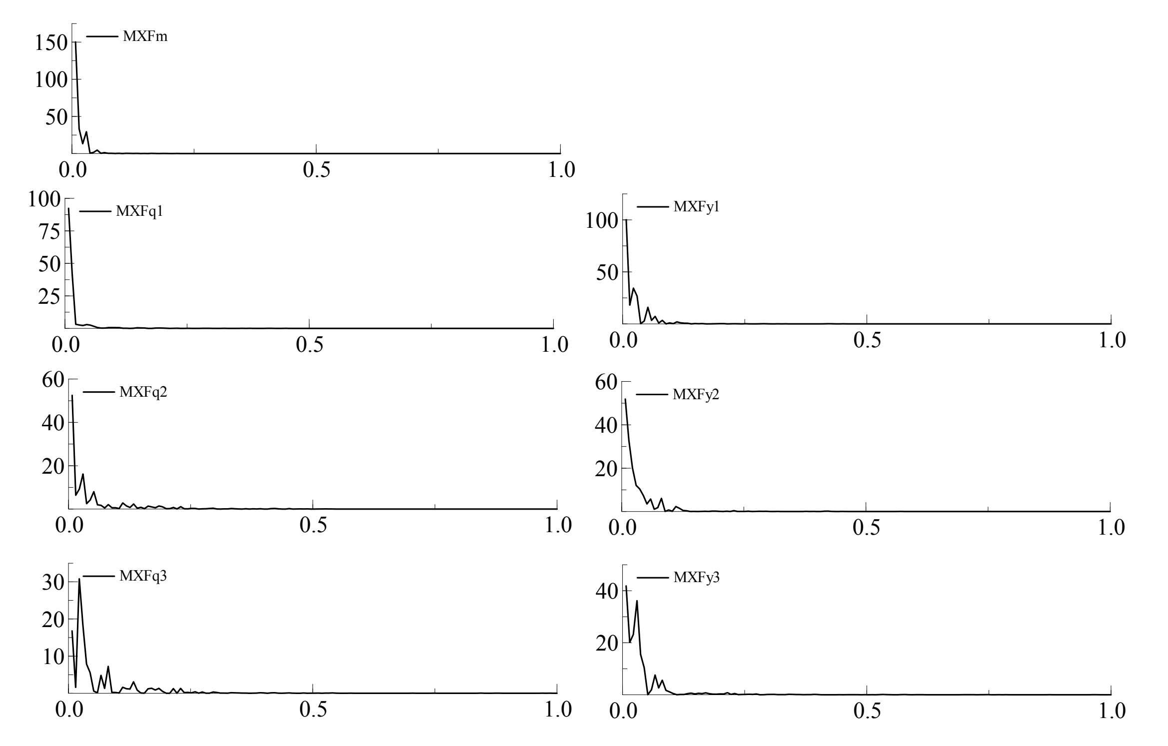
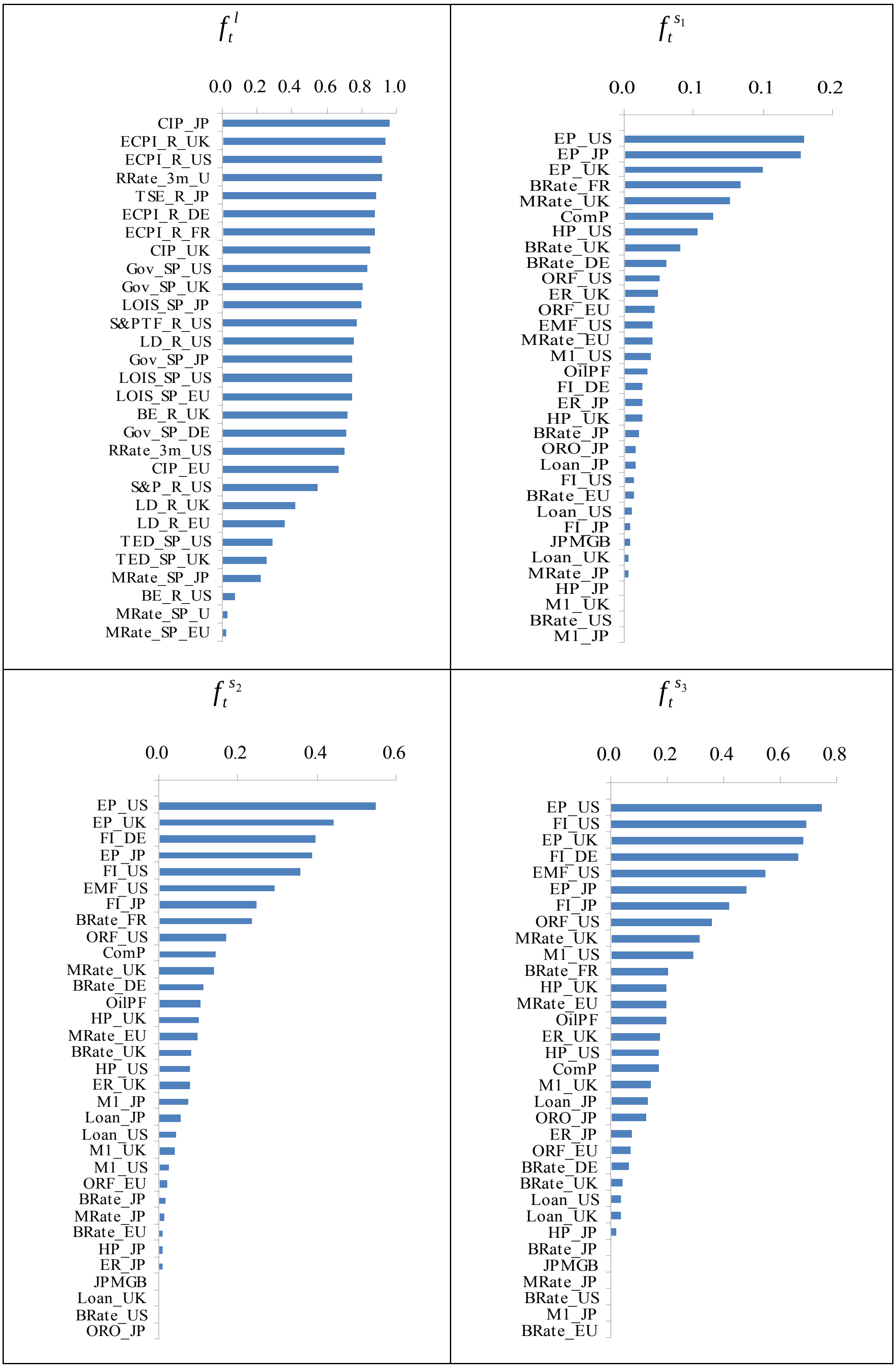
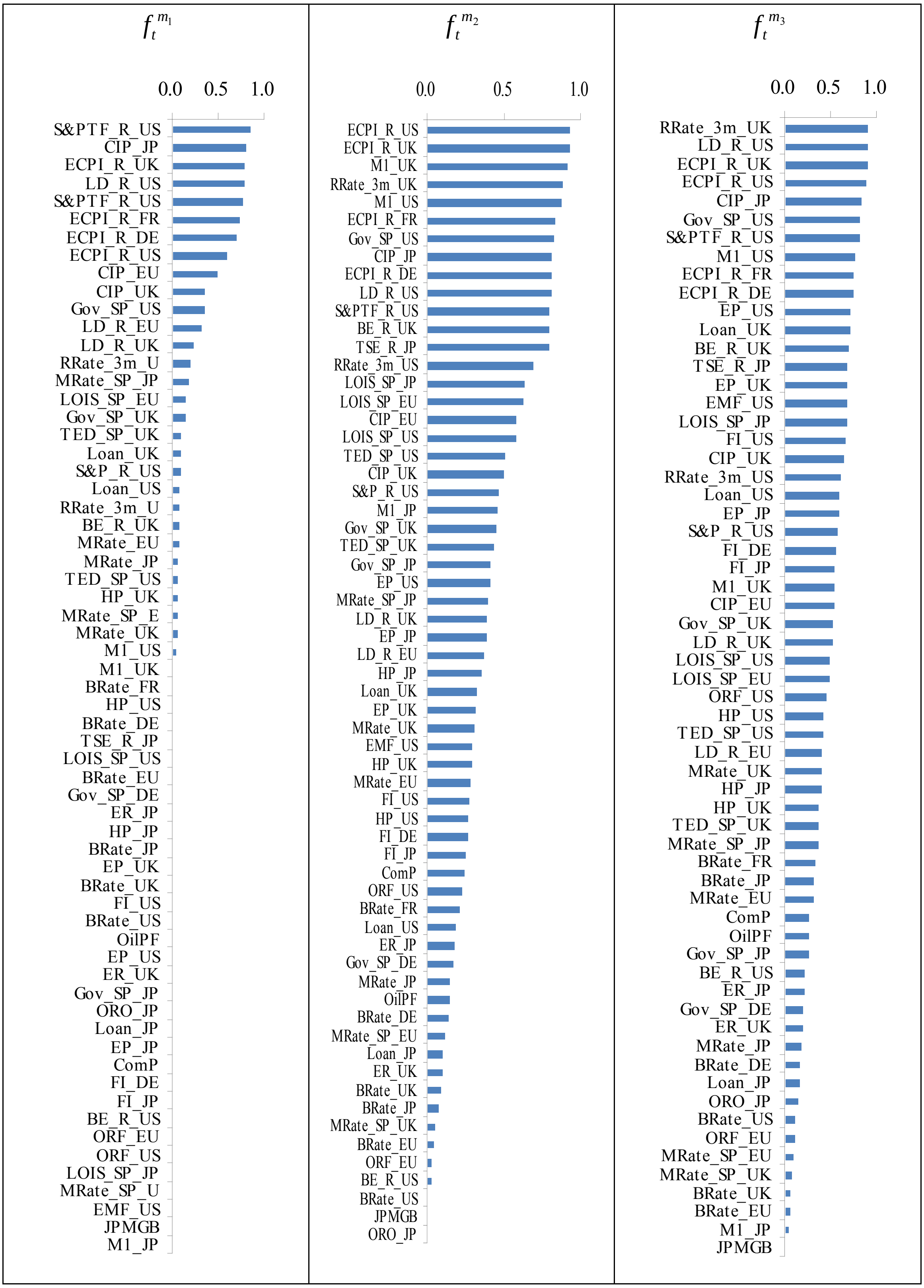


Figure 3.1 Communality coefficients of the indicators in the separate case



Note: The communality coefficient is the sum of the squared factor loadings for all factors for a given indicator. It measures the percent of variance in a given indicator explained by all the factors jointly and may be interpreted as the reliability of the indicator.

Figure 3.2 Communality coefficients of the indicators in the mixed case



Note: see the note in Figure 3.1.

Figure 4 The four target variables for forecasting

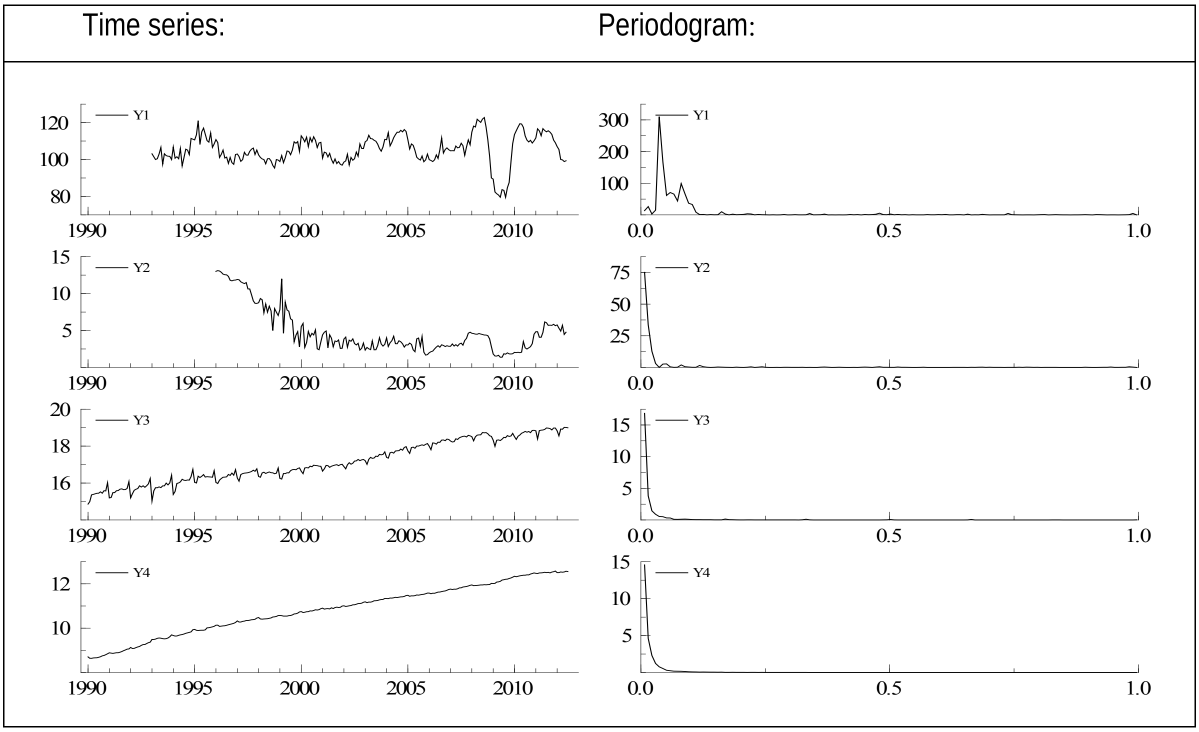
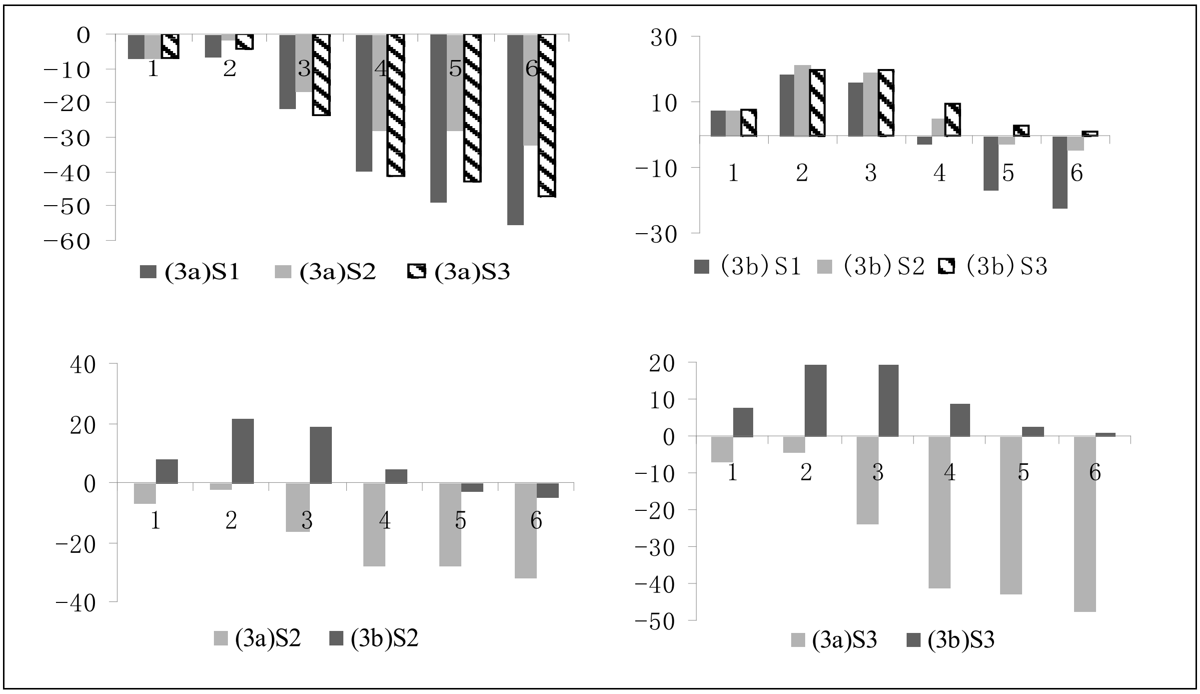
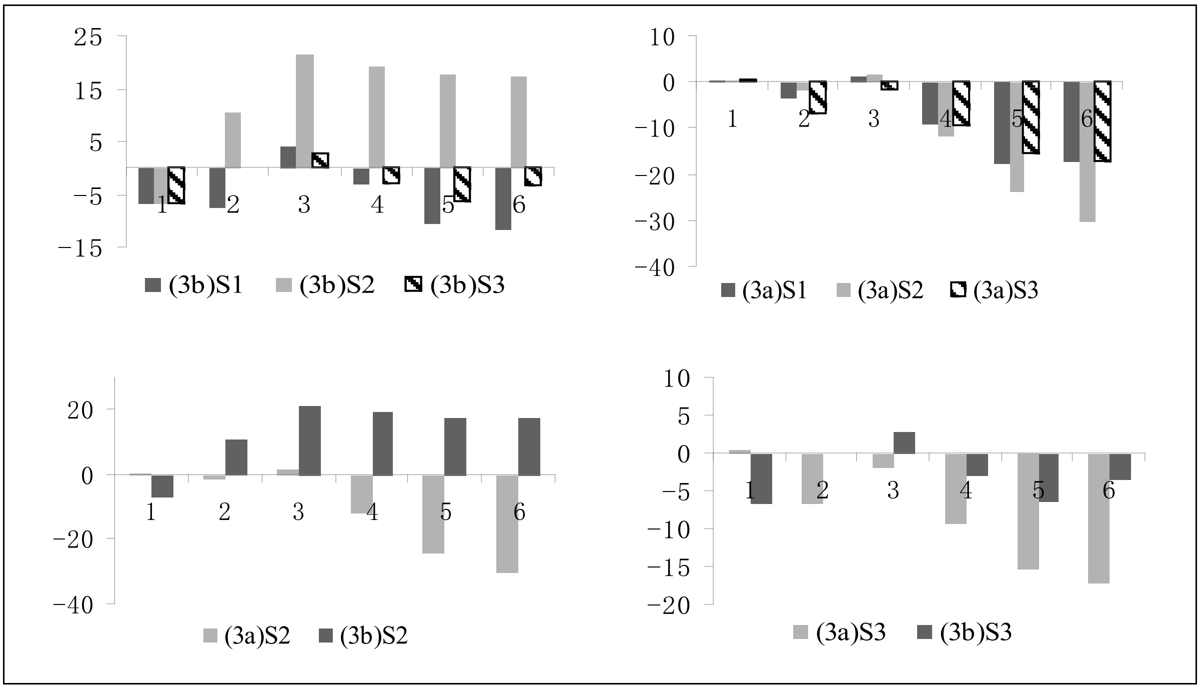


Figure 5.1 RMSFEs of (3a) and (3b) as the percentage deviations from the RMSFEs of the benchmark model under the three scenarios: The import price equation, y_1



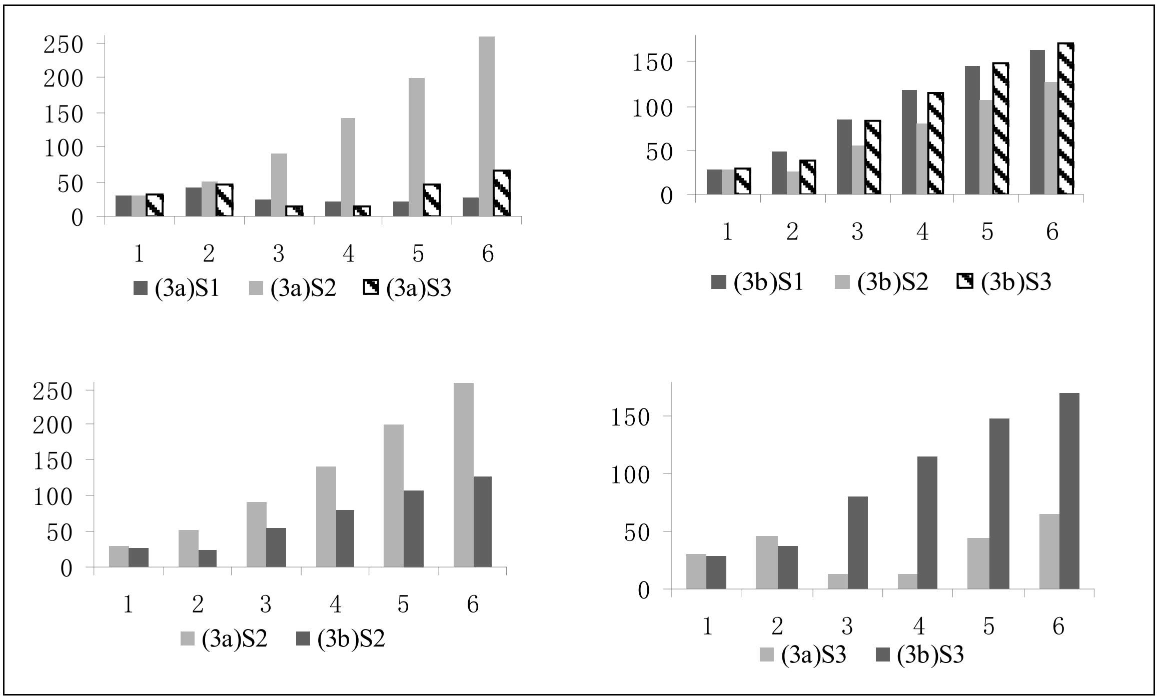
Note: See Table 8.1 for the formula of the percentage deviations; S1, S2 and S3 denote scenarios one, two and three respectively.

Figure 5.2 RMSFEs of (3a) and (3b) as the percentage deviations from the RMSFEs of the benchmark model under the three scenarios: The interest rate equation, y_2



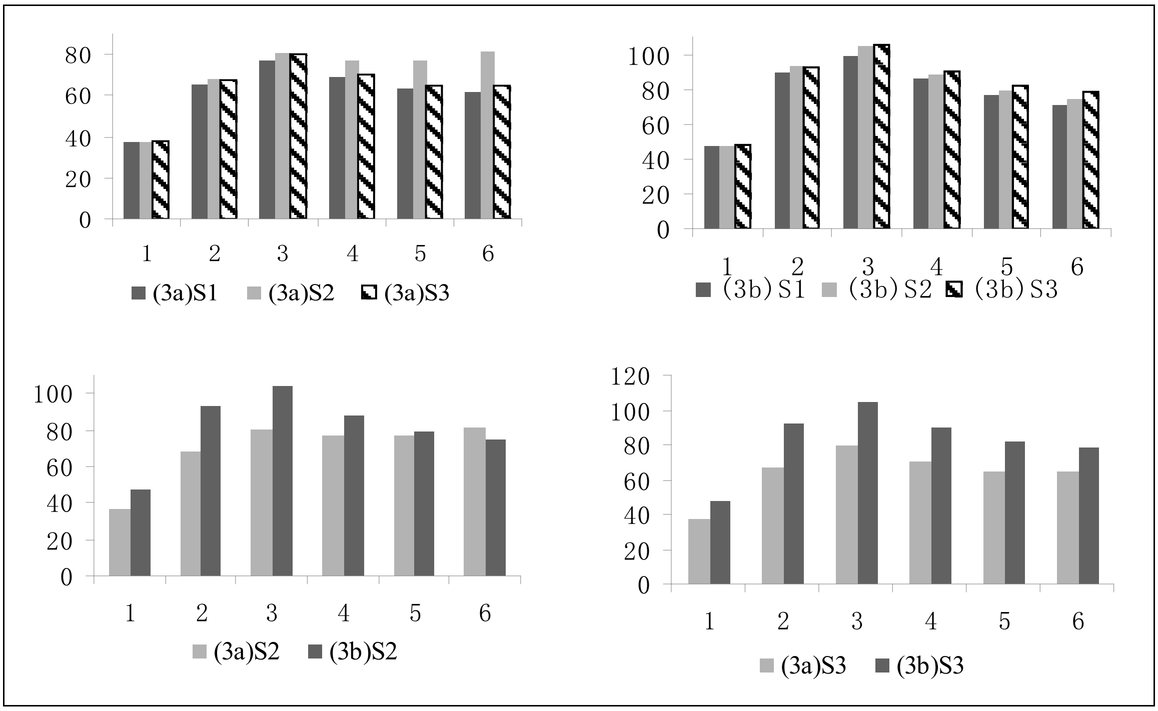
Note: The same as Figure 5.1.

Figure 5.3 RMSFEs of (3a) and (3b) as the percentage deviations from the RMSFEs of the benchmark model under the three scenarios: The export equation, y_3



Note: The same as Figure 5.1.

Figure 5.4 RMSFEs of (3a) and (3b) as the percentage deviations from the RMSFEs of the benchmark model under the three scenarios: The M1 equation, y_4



Note: The same as Figure 5.1.

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