Forecasting Financial Crises and Contagion in Asia using Dynamic Factor Analysis

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Abstract

In this paper we use a Dynamic Factor model to retrieve vulnerability indicators able to predict financial turmoil. A stochastic simulation experiment is then used to produce the corresponding probability forecasts regarding the currency crisis events affecting a number of East Asian countries during the 1997-1998 period. The Dynamic factor model improves upon a number of competing model, in terms of out of sample forecasting performance.

Keywords: Financial Contagion, Dynamic Factor Model
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1 Introduction

The recent currency and financial turmoil affecting the Latin American countries during the 1994 period and the East Asian emerging market economies during the 1997-1998 period has attracted particular attention by both academics and policymakers. In particular, these crises have fuelled a new variety of theories, also known as third generation of currency crisis model, which focus on moral hazard and imperfect information. The emphasis is on excessive booms and busts in international lending. In particular, throughout most of the 1990s, massive capital inflows had been pouring in the East Asian region, mainly in the form of bank lending. Most of the foreign borrowing in these economies was short-term with Japan being the country with the largest exposure. Therefore, the focus of this paper is to examine the role played by the financial capital markets in propagating balance of payment crises across Indonesia, Malaysia, Philippines, Korea, Thailand, during the 1997-1998 crisis period. The third generation of currency crisis models has then motivated various reports

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from the IMF on the "architecture" of the international financial system, where the emphasis is on the importance of sound debt and liquidity management in helping to prevent external crises. For instance, the IMF report on "Debt- and Reserve-Related Indicators of External Vulnerability", 2000 stresses the importance of holding foreign reserves for Central Banks in order to maintaining liquidity and allowing time to absorb shocks in situations where access to borrowing is curtailed or very costly. It is, therefore, important to monitor a number of vulnerability indicators (such as the ratio of either the total stock of external debt to the stock of international reserve or the ratio of the short term external debt to the stock of foreign reserves) to examine whether they can be considered as accurate leading indicator of currency crisis, as suggested by the Early Warning Signal literature, EWS.

Most of the EWS studies are based upon the in sample forecasting performance of a variety of indicators regarding country specific currency crises. The focus of this paper is on the out of sample leading indicator properties of a number of variables regarding country specific currency crises. In particular, the choice of the variables to be included in the dataset is based upon the suggestion given by the studies on financial contagion. The literature on financial contagion puts the emphasis on the role of the geographical composition of external debt (e.g., the common lender channel), and on the maturity mismatch in explaining the spread of the crisis hitting one country to other countries. In this paper we control for these financial channels exploiting detailed information provided by the Bank for International Settlements, BIS on the composition of the external debt In particular, we employ a Dynamic Factor model, DF, where the dynamics of the large number of data for the countries under investigation is summarised by few factors. It is important to observe that given BIS external debt data are available only at low frequency, the number of cross sections exceed the time series observations, and it is not practical to use standard state space model methods to extract factors. Therefore, the factor extraction occurs by standard principal components analysis as suggested by Stock and Watson (2002). The DF model is used to produce forecasts for currency crisis events, through, first, a latent variable identified as a regional vulnerability indicator. Furthermore, we also show how forecasts associated with each variable included in the large dataset considered can be obtained through the DF model.

The variable to be predicted in this paper is the Exchange Market Pressure Index (EMP), which is commonly used to proxy of stress on the foreign exchange market. This index was first used by Girton and Roper (1977), and subsequently by a number of authors in the context of exchange rate crisis (see Tanner (2002), for a recent use). Girton and Roper use a simple monetary model to derive a definition of EMP as the sum of exchange rate depreciation and reserve outflows, scaled by base money. This index summarizes the flow of excess supply of money (e.g., the difference between the growth rates of the domestic component of the monetary base and money demand) in a managed exchange rate regime, reflected in both exchange rate and reserve movements. Hence an increase in the value of a country's EMP indicates that the net demand for that country's currency is weakening and hence that the currency may be liable to a speculative attack or that such an attack is already under way.

The (out of sample) probability forecasts regarding the likelihood of the crisis are obtained by implementing stochastic simulation of the estimated DF model, and their accuracy is based upon the Kuipers Score (KS) method.

The outline of the paper is as follows. Section 2 and 3 review the EWS literature and the financial contagion studies, respectively. Section 4 describes the empirical methodology. Section 5 describes the dataset and the empirical analysis. Section 6 concludes.

2 Early Warning System

Two are the main methods used in the EWS literature. First, one may use the signal approach proposed by Kaminsky et al. (1998) who monitor the evolution of several indicators. If any of the macro-financial variables of a specific country tends to exceed a given threshold during the period preceding a crisis, then this is interpreted as a warning signal that a currency crisis in that specific country may take place within the following months. The threshold is then adjusted to balance type I errors (that the model fails to predict crises when they actually take place) and type II errors (that the model predicts crises which do not occur). In the signal approach, both the crisis indicator, defined as an episode in which an Exchange Market Pressure index, EMP (see below), exceed a threshold and the explanatory variables are dummy variables, taking value 1 only during the crisis period. Kaminsky and Reinhart (2000) and Goldstein et al. (2000a) base their prediction of a crisis occurring in a specific country by monitoring the evolution not only of country specific indicators, but also of macro-variables in other countries. The authors (op. cit.) find that, adding information about crisis elsewhere, reduces the prediction error, even after the fundamentals have been accounted for. The gains from incorporating information on crises elsewhere are highest for Asia.

The alternative method in EWS literature, is to use limited dependent regression models (logit or probit) to estimate the probability of currency crisis. The currency crisis indicator is modeled as a zero-one variable, as in the signal approach. However, unlike in the signal approach, the explanatory variables do not take the functional form of a dummy variable, but enter the model mostly in a linear fashion. The prediction of the model is interpreted as the probability of a crisis. In particular, the study of Van Rijckeghem and Weder (2000) uses a multivariate logit or probit model to pooled panel data from industrialised and emerging market economies. Jacob, Kuper and Lestano (2004) also apply discrete choice models to panel data for Indonesia, South Korea, Malaysia, Philippines, Singapore, and Thailand. The authors (op. cit.), in their analysis, use as regressors the principal components extracted from the small dataset of macro-variables of a specific country.

All the aforementioned studies rely on in sample forecasting. The study of Berg and Pattillo (1999) examine the out of sample prediction performance of both the aforementioned EWS methods regarding the 1997 Asian crisis period. As for the signalling approach, most (68%) crises were not signalled in advance, and most (60%) of the signals were false (the results improve slightly if the current account relative to GDP and the level of the M2/reserves ratio are included). Nevertheless, the predictions were better than random guesses. As for the probit regression model, Berg and Pattillo (1999) find that, out of sample, 80% of crises and 79% of tranquil periods are correctly called. More recently, Berg et al. (2004) assess the (out of sample) predictive performance of a number of EWS model based indicators. These models are those used by the IMF (such as the one developed by Kaminsky et al.,1998), and those developed by Goldman Sachs and of Credit Suisse First Boston. Berg et al. (2004) compare the EWS model forecasts to non-model-based indicators such as bond spreads, agency ratings, and risk scores published by analysts. More specifically, they monitor the forecasting performance of the various indicators from 1999 onwards. The focus of our study is on the accuracy of out sample forecasts regarding also the Asian currency turmoil period of 1997-1998.

Also, Goldstein et al (2000b) and Zhuang and Dowling (2002) find some support (in terms of the out-of-sample predictive performance) for the use of a EWS based upon the signaling approach. In Goldstein et al (2000b), the crisis indicator is defined with respect to an EMP index, whereas in Zhuang and Dowling (2002) is defined as an episode of monthly nominal depreciation against the US dollar exceeding a given threshold.

Finally, in Chauvet and Dong (2004), a factor model with Markov regime switching dynamics is used to construct leading indicators of the East Asian currency crises. The main advantage of their model specification is that it treats foreign exchange market regimes as unobservable priors instead of observed ex post events, and no ad hoc criterion is adopted in determining the crisis state. However, the crisis event is only defined in terms of nominal exchange rate depreciation. Also, the latent variable extracted captures the comovement of only few nominal-financial variables, ignoring, the important role of the geographical and maturity composition of the external debt to the development of a balance of payment crisis event. The empirical model successfully produces early probabilistic forecasts of the Asian currency crises, and these results hold for both in-sample and recursive out-of-sample estimation.

3 Financial contagion

In this section we review the theoretical literature on financial contagion. Calvo-Reinhart (1996) distinguish between fundamental based contagion and true contagion. The former one arises when the country hit by a financial crisis is linked to the others via trade or finance. The latter arises when common shocks to the aforementioned channels are either not present or have been controlled for. As for the role of (financial) common shocks played in spreading turbulence across the East Asian region, a great deal of attention has been devoted to the common lender channel (see the theoretical study of Schinasi and Smith, 1999). Specifically, when a common lender country is highly exposed to a crisis country, it is likely to shift away from lending and to cut its lending to other countries in order to restore its capital adequacy. As suggested by Sbracia and Zaghini (2000), common lender channel effect can also operate through the value of collateral (e.g. stocks or government bonds) provided by borrowers. Consider a region that is economically open but has an underdeveloped bank based financial market, and suppose that an economy in this region backs its funding by asset holdings in a neighbouring country. When a crisis hits the "collateral" economy, the lender will require a sounder backing of its claims. If this is impossible, the lender will downgrade the borrower and reduce the amount of credit issued, and it will spread the crisis internationally. Furthermore, as Kaminsky and Reinhart (2001) point out, given that the developed countries' loan contracts were of short maturity, the lending country rebalancing needs might imply not only the refusal to extend new credits to the other borrowers, but also the refusal to roll-over their existing loans. The empirical studies of Kaminsky and Reinhart (2000), and Van Rijckeghem and Weder (2000) find evidence of the role played by commercial banks in spreading shocks and inducing a sudden stop in capital flows in the form of bank lending.

Other studies stress on the importance of capital market in spreading turbulence internationally. Calvo and Mendoza (1999) present a model where the fixed costs of gathering and processing country-specific information give rise to herding behavior, even when investors are rational. Kodres and Pritsker (1999) also present a model with rational agents and information asymmetries, where financial investor are engaged in cross market hedging. Calvo (1999) stresses on the role played by margin calls in one market requiring that leveraged informed investors liquidate many positions, causing financial contagion. In this case, uninformed investors may mimic informed investors even though ex post it turns out that no new information about fundamentals was revealed.

To summarise, the literature on financial contagion reviewed suggests to pay particular attention to the overall size of the external debt (relative to the stock of foreign reserves) and also on debt maturity and geographical composition (see the description of the dataset below).

4 Empirical methodology

In this section we describe the Dynamic Factor model (see Stock and Watson, 2002) which allows to pool the whole set of information provided by the different vulnerability indicators in each country. We will show how the DF model can be used to predict currency crisis events by either building a vulnerability indicator common to whole East Asian region or by measuring the contribution of each variable included in the large dataset under investigation to forecasting the EMP index. Kaminsky and Reinhart (2000) who use a signal based method were the first (through in sample forecasting) to find important the role played by a regional vulnerability component in explaining the exchange market pressure. More recently, Mody and Taylor (2003) have used a Dynamic Factor model to extract a measure of regional vulnerability in a number of emerging market countries. The authors (op. cit.) analysis (based upon Kalman filter estimation of state space models) relies on in sample prediction and ignores the geographical composition and maturity structure of external debt. In this paper we use disaggregate data on the external debt (available from the Bank of International Settlements, BIS). The BIS dataset is available for a relatively long data span (starting from 1983) only at low frequency (bi-annual basis). Consequently, the number of cross sections exceed the time series dimension and it is not practical to use standard state space model methods to extract factors. Therefore, in this paper, the factors extracted from the large dataset considered are obtained using principal components analysis as suggested by Stock and Watson (2002)[1]. We now describe the Dynamic Factor modelling approach to a large dataset.

4.1 Model specification for a large dataset

The interdependence among the different variables in the system is described by the following Dynamic Factor model:

$$x_t = \Gamma f_t + \xi_{nt} \tag{1}$$

where x_t is an $n \times 1$ vector of variables observed at time t; f_t is the r dimensional vector of factors (latent variables), with $r << n$; Γ is an $n \times r$ matrix of factor loadings. In the first stage of the analysis, each series is de-meaned and divided by the corresponding sample standard deviation. Then, we apply principal component analysis to the standardised $T \times n$ panel x. The factors estimates are given by $\sqrt{T}W$, where the matrix W is $T \times r$, and it has, on the columns, the eigenvectors corresponding to the first r largest eigenvalues of the sample covariance matrix Ω for x.

4.2 Model specification for the factors

Following Forni et a. (2003), the dynamics of the factors is described by:

$$f_t = D f_{t-1} + \varepsilon_t \tag{2}$$

where D is the $r \times r$ autoregressive coefficients matrix and ε_t is an $r \times 1$ vector of (reduced form) innovations. The coefficients matrix D and the residuals ε_t of the VAR(1) model in (2) are estimated by OLS (once the r factors f_t have been retrieved in the first stage of the analysis). Then, an $r \times q$ matrix R is obtained using the following eigenvalue-eigenvector decomposition of Σ (which is the sample covariance matrix for the innovations in 2):

$$R = KM \tag{3}$$

In particular, M is a diagonal matrix having the square roots of the q largest eigenvalues of Σ on the main diagonal; K is an $r \times q$ matrix whose columns are the eigenvectors corresponding to the q largest eigenvalues of Σ. The matrix R measures the relationship between

[1]The Stock and Watson (2002) method is a time-domain based approach. In Forni, Lippi, Hall, and Reichlin (2003) the factor extraction using an a frequency domain based approach. Finally, Kapetanios and Marcellino (2003) use an approach based upon a state space model.

the r dimensional vector of reduced form innovations ε_t and the q dimensional vector of common shocks u_t(with $q < r$):

$$\varepsilon_t = Ru_t \tag{4}$$

From equations (2) and (4) we can observe that the matrix R measures the impact of the common shocks u_t on each factor f_t and it is crucial in retrieving the impact of the common shocks u_t on each series of the dataset x (via equation 1).

4.3 Forecast under alternative scenarios: stochastic simulation of DF model

Given that crisis events are related to the distribution tail of the EMP index, the focus of the forecasting exercise in this paper is not on average scenarios, but on the adverse realisations of shocks either common or specific to each variable in the dataset x. For this purpose, in this section we show how to obtain predictions (corresponding to adverse scenarios) from the Dynamic Factor model described. The first model we consider is the augmented Dynamic Factor model (see Stock and Watson, 2002) which gives the following projection of the (unstandardised) EMP index:

$$EMP_{i,t+1} = const + \sum_{k=1}^{p} \alpha_k EMP_{i,t+1-k} + \beta_i \hat{f}_{t+1} \; + \nu_{i,t+1} \tag{5}$$

In this model, $\hat{f}_{t+1}$is the one step ahead prediction for the r factors. In particular, the loading of the factors into the (unstandardised) EMP_i index is captured by the $1 \times r$ vector of coefficients β_i. In order to account for serial dependence of the dependent variable, the factor projections are augmented with past values of the dependent variable. The residual $\nu_{i,t+1}$is the idiosyncratic country specific shock.

The projection $\hat{f}_{t+1}$ is obtained by shifting equations (2) and (4) one period ahead and by replacing them in (5):

$$EMP^u_{i,t+1} = \left[const + \sum_{k=1}^{p} \alpha_k EMP_{i,t+1-k} + \beta_i (Df_t + Ru_{t+1}) \right] + \nu_{i,t+1} \tag{6}$$

The term in the square brackets of the r.h.s. of equation (6) is the one step ahead projection of the systemic component of the EMP index under different scenarios[2]. The

[2] Given that we consider the BIS data available only at bi-annual frequency, the one step ahead forecasts correspond to an horizon of six months.

scenarios are given by different realisation of the common shocks, u_{t+1}. In particular,the expression in brackets can be split in two components. The first addend is given by $const + \sum_{k=1}^{p} \alpha_k EMP_{i,t+1-k} + \beta_i D f_t$, and it denotes the anticipated component (at time t) of the EMP index. The second addend in the brackets, $\beta_i R u_{t+1}$, accounts for the unanticipated impact of the common shock occurring at time $t+1$. The last term in (6) measures the idiosyncratic component in the projection equation given by different realisation of the country specific shock $\nu_{i,t+1}$.

In order to produce the prediction given by equation (6), we need, first, to determine the number of factors r and the number of lags p for the dependent variable. Fixing the maximum order for p and r, to four and eight, respectively, we use a Bayesian information criterion, BIC as suggested by Stock and Watson, (2002). Secondly, after determining the number of factors, we need to obtain their estimates and those for the coefficient matrices D and R, following the procedure described above. Then, the coefficient estimates for $const$, α_k and β_i are obtained by regressing (via OLS) the (unstandardised) EMP index on an intercept, its lags, and on the estimated factors.

It is important to observe that the coefficient estimates (and, also the BIC selection criterion) are obtained using a recursive OLS, so as to avoid using future information in the forecasting exercise.

Finally we employ the method of Monte Carlo stochastic simulation in order to generate the different scenarios. In particular, each scenario is given by a combination of realisation of the common (which is, then, interpreted as the regional vulnerability indicator) and idiosyncratic shocks, u and ν_i, respectively. Both shocks are obtained from draws from $N(0,1)$ random variables. The number of replications (hence the number of different scenarios) is 10000. We argue that, for the purpose of forecasting, it is the choice of r and not of q that impact on the forecasting results. Any choice of q (e.g. the dimension of the structural form common shocks vector) would imply a different R such that the vector of reduced form disturbances is unchanged. Therefore, we fix q to 1 the number of common shocks u describing a specific scenario. This will allow to reduce the computational intensity of the Monte Carlo experiment by considering 10000 replications as an exhaustive number of scenarios.

We are also interested in producing projections associated with different realisation of each variable, included in the dataset x. For this purpose, we can still use the Dynamic Factor model described in (1). The prediction at time $t+1$ of the j^{th} component in x can be specified, according to the model given by the common component of the panel x in (1), and by (2), and (4) as:

$$x_{j,t+1} = \Gamma_j (Df_t + Ru_{t+1}) \tag{7}$$

where Γ_j is the j^{th} row of the (standardised) loading factor matrix in (1). More specifically, if we rearrange (7), then we obtain:

$$u_{t+1} = (\Gamma_j R)^{-1} x_{j,t+1} - (\Gamma_j R)^{-1} \Gamma_j D f_t \tag{8}$$

If we replace (8) in (6), then we obtain:

$$\begin{aligned} EMP_{i,t+1} = & \left\{ const + \sum_{k=1}^{p} \alpha_k EMP_{i,t+1-k} + \beta_i \left[Df_t - R(\Gamma_j R)^{-1} \Gamma_j D f_t \right] \right\} \\ & + \beta_i R (\Gamma_j R)^{-1} x_{j,t+1} + \nu_{i,t+1} \end{aligned} \tag{9}$$

The expression in parenthesis captures the EMP index anticipated component, whereas the last two terms in (9) capture the EMP index unanticipated component. We can observe that the unanticipated component is driven by the effect of a country specific shock to the EMP index, $\nu_{i,t+1}$, and by $\beta_i R(\Gamma_j R)^{-1} x_{jt+1}$. The latter measures the unanticipated impact of a shock $x_{j,t+1}$ (specific to each variable considered in the dataset x) on the EMP index . The stochastic simulation experiment can be described as follows. Each scenario is given by a combination of realisations of a shock to the j^{th}variable in the dataset x and of a country specific shock to the EMP index. Both innovations are obtained from draws from an *iid*, $N(0, 1)$ distribution[3]. The number of replications (hence the number of different scenarios) is 10000.

To summarise, the construction of currency turmoil leading indicators through the DF model (which are either the factors $\mathbf{f_t}$, or, in our simulation experiment, the common shock u) is achieved by choosing weights for each specific time series in the dataset so that the noise to signal ratio is minimised. The weights can then be assembled to build a composite vulnerability indicator (e.g. the common shock u) and to produce the forecasts described by (6). Alternatively, an appropriate chosen weight (see 9) can be attached to a specific variable in the dataset in order to produce the predictions given by (9).

[3]We also consider the x_j shocks as contemporaneously correlated by replacing the iid, N(0,1) $x_{j,t+1}$ innovations with z where z is obtained by picking the j^{th} row of the Cholesky decomposition of Ω and multiplying it by an $n \times 1$ vector of *iid*, $N(0, 1)$ shocks. The forecasting results (available upon request) do not change.

4.4 Forecast under alternative scenarios: stochastic simulation of competing models

The (out of sample) forecasting performance of the various specifications associated with the Dynamic Factor model is compared with various competitor models given below:

1. The first model we consider is an optimal AR, which gives the following projection:

$$EMP_{i,t+1}^{AR} = \sum_{k=1}^{p} \alpha_k EMP_{i,t+1-k} + \nu_{i,t+1} \tag{10}$$

   where the lag order k for the AR model specification is obtained through recursive BIC (with the coefficients α_k estimated by recursive OLS). The maximum order for the lags of the dependent variable, when using the BIC criterion, has been fixed to four. The scenarios associated with (10) are obtained through 10000 draws from an $N(0,1)$ distribution of the idiosyncratic shock ν_i.

2. The second class of models is given by an Autoregressive Distributed Lag model, $ARDL$l:

$$EMP_{i,t+1}^{ARDL} = \sum_{k_1=1}^{K_1} \alpha_{k_1} EMP_{i,t+1-k_1} + \sum_{k_2=1}^{K_2} \alpha_{k_2} exog_{j,t+1-k_2} + \nu_{i,t+1} \tag{11}$$

   where the lag orders k_1 and k_2 are selected using recursive BIC (fixing the maximum lag order to 4). The projection equation (11) allows to check whether current and past values of $exog_j$ (e.g. the j^{th} variable entering in the dataset x) improves upon the AR, in terms of forecasting performance. The coefficients α_{k_1} and α_{k_2} are estimated by recursive OLS. The scenarios associated with (11) are obtained through 10000 draws from an $N(0,1)$ distribution of the idiosyncratic shocks ν_i. We can observe that the contribution of $exog_i$ to the prediction of EMP in equation (11) is treated as deterministic.

3. The third class of models we consider are:

$$EMP_{i,t+1}^{ARDL} = \sum_{k_1=1}^{K_1} \alpha_{k_1} EMP_{i,t+1-k_1} + \sum_{k_2=1}^{K_2} \alpha_{k_2,ex} exog_{j,t+1-k_2} + \alpha_{1,ex} z_{j,t+1} + \nu_{i,t+1} \tag{12}$$

$$\begin{aligned} EMP_{i,t+1}^{ARDL} = & \sum_{k_1=1}^{K_1} \alpha_{k_1} EMP_{i,t+1-k_1} + \sum_{k_2=1}^{K_2} \alpha_{k_2,ex} exog_{j,t+1-k_2} \\ & + \alpha_{1,ex} [chol(\Omega)]_j z_{t+1} + \nu_{i,t+1} \end{aligned} \tag{13}$$

Contrary to equation (11), we treat as stochastic (e.g. depending on a specific scenario) the contribution of $exog_j$ to forecasting the EMP index in eqations (12) or (13). In particular, in eq.(12), the current value of $exog_j$ is shocked through an *iid* N(0,1) innovation. In (13), the current value of $exog_j$ is shocked through an innovation which accounts for the interdependencies across the different variables in the dataset x. This is modelled by picking the j^{th} row of the Cholesky decomposition of Ω (e.g. the sample covariance matrix of the dataset x) and by multiplying the latter by z, which is the n dimensional vector of *iid* and contemporaneously uncorrelated N(0,1) shocks.

It is important to observe that results for any of the models considered above would not change if the Monte Carlo experiment is based upon draws from a t distribution with k degrees of freedom[4]. This would suggest that the DGP for the different EMP indices at low frequency (given bi-annual observations) is well proxied by a Gaussian distribution.

4.5 Out of sample probability forecast and forecast accuracy evaluation

In this paper, the crisis events are defined by the observations of the EMP index taking values of 1.5 standard deviation above the mean. Therefore, the realisation of the EMP index which call a crisis event are: a) semesters 1998:1 and 1998:2 for Indonesia; b) semester 1998:1 for Malaysia; c) semester 1998:1 for Philippines; d) semesters 1998:1 and 2001:2 for Korea; e) semesters 1997:2 and 1998:2 for Thailand. In this section we, first, describe how to obtain the probability forecasts.

We consider as a forecast evaluation period the one given by the last 20 periods (e.g. 10 years) in the sample. For each of the 20 periods, we carry Montecarlo stochastic simulation in order to generate the alternative scenarios corresponding to model chosen using the BIC criterion. The probability forecasts are obtained by counting the number of times the prediction given by any of the forecasting models employed is equal or above 1.5 standard deviation from the mean of the actual realisations of the corresponding EMP index. The resulting number is then divided by the total number of scenarios (e.g. 10000). Therefore, we argue that the method suggested, in this paper, to compute the probability forecasts, implicitly accounts for only adverse economic scenarios. These are given by adverse realisations of shocks to the various vulnerability indicators.

[4]The results based upon Gaussian draws are reported in Table 1 and 2. The results associated with draws from t student with 3, 5, 10 degrees of freedom are available upon request.

In order to evaluate the accuracy of probability forecasts, we employ the Kuipers Score (Granger and Pesaran, 2000) based on the definition of two states as two different indications given by the model: currency crisis and no currency crisis. We assume that the model signal the crisis when the predicted probability is larger than 0.5. Therefore, one can calculate event forecasts $(E_t) : E_t = 1$ when $P_t > 0.5$ and $E_t = 0$ when $P_t \leq 0.5$. Comparing these events forecasts with the actual outcomes R_t, the following contingency matrix can be written:

Forecasts/Outcomes	crisis($R_t = 1$)	no crisis($R_t = 0$)
crisis	Hits	False Alarms
no crisis	Misses	Correct Rejections

The Kuipers score is defined as the difference between the proportion of crises that were correctly forecasted, $H = hits/(hits + misses)$ and the proportion of no crisis that were incorrectly forecasted, $FA = false\ alarms/(false\ alarms + correct\ rejections)$:

$$KS = H - FA \tag{14}$$

Positive values for the KPS scores imply that: a) at least, one crisis event is correctly signalled; b) the model generates proportionally more hits than false alarms.

5 Empirical analysis

5.1 The Data

As explained in section 2, given the important role of the total external debt (not only its size, but also its geographical composition and its maturity structure) in explaining the financial soundness of a particular economy, we need to retrieve disaggregated data on external debt. In particular, to construct these indicators, we use the consolidated statistics on external debt obtained from the Bank of International Settlements (BIS) on bi-annual basis from Q4:83 to Q1:2004 in millions of US dollars, for a total of 42 time series observations[5]. These data measure, on a worldwide consolidated basis, the foreign claims of banks headquartered in the reporting area. Beyond the total external (banking) debt measures for each country, we use the following disaggregate data on external borrowing from developed countries banks.

First, an important component of the consolidated banking statistics are the foreign claims of BIS reporting banks vis-a-vis individual countries. As explained above, it is important to gauge information on the distribution of bank claims by nationality of bank, in order to measure potential contagious effects operating through a common creditor channel. We concentrate on external borrowing from: Belgium, France, Germany, Italy, Japan,

[5] These data are also available on quarterly basis from 1999

Netherlands, Sweden, Switzerland, UK, and the US. Secondly, in light of the discussion above it is also important to have information on the external debt maturity structure. The consolidated banking statistics provide data on the total external debt with maturity: up to and including one year; over one year up to two years; over two years.
We consider the external borrowing of the private sector (banks and non banks) and of the public sector of each country from developed countries banks. In order to complete the dataset describing thoroughly the external banking debt of the countries under investigation we also include undisbursed credit commitments and local currency claims on local residents. Furthermore, we include data on international bonds and notes issued by the five Asian emerging economies under investigation.

We also include the money supply aggregate M_2 (obtained from the International Financial Statistics, IFS, database of the IMF) of each country, and we convert each aggregate into US dollars using the nominal exchange rate of the country versus US dollars. Each money based indicators of reserves provide a measure of the potential for resident-based capital flight from the currency, since it is argued that, an unstable demand for money or the presence of a weak banking system indicates a greater probability of such capital flight. We also consider the total amount of imports (measured in millions of US dollars) of each of the five countries under investigation.

Each of the aforementioned variables (in US dollars) is deflated by the country specific stock of official reserves foreign exchange reserves (minus gold) in millions of US dollars in order to obtain indicators of vulnerability.

The data for the components of the EMP index are obtained from the International Financial Statistics (IFS) of the IMF database. As suggested by Girton and Roper (1977), the measure of the EMP index consists of a weighted sum of the exchange rate depreciation (measured as unit of domestic currency per US dollar), and US dollar denominated official reserves (minus gold) outflows scaled or reserve money (converted in US dollars) of the previous period. The weights chosen that each of the two components has a standard deviation of unity, in order to preclude any of them from dominating the index.

Finally, the EMP index of each country is also included in the dataset to account for the role played by foreign currency mismatches in predicting a crisis event. This will give a total of the 115 variables constituents of the dataset under investigation (see the Data Appendix for a description of the variables).

5.2 Empirical Results

As mentioned, the out of sample probability forecast are obtained through recursive OLS estimation. In particular, we use data available through the first semester of 1994 and then we use the estimated model to produce the second semester of 1994 probability forecast (see below). This is repeated throughout the sample, moving ahead one semester. This gives the forecast evaluation period equal to 20 observations.

The KPS scores corresponding with the predictions obtained from common systemic shock u, using the Dynamic Factor model in equation (6), are 0.44, 0.89, -0.05, 0.44, and 0.44. for Indonesia, Malaysia, Philipines, Korea and Thailand, respectively. In Table 1 we report the KPS scores obtained using the projections given by (9). These are the Dynamic Factor implied projections associated with the j^{th} variable in the dataset, with the shocks $x_{j,t+1}$ drawn from an iid, $N(0,1)$ distribution. Overall, the forecasts associated with the regional vulnerability indicator (see equation 6) or with each individual variable as implied by the DF model as described by (9) are able to call currency turmoil correctly (most of the times) and also to score positive values for the KPS statistic[6].

We do not report the forecasting results associated with the models given by equations (10), (11),12 and (13), given that the corresponding KPS scores are always zero. Even though the forecasts corresponding to these benchmark models do not lead to false alarms, they are not capable to call correctly a crisis. The Philippines is the only country where the probability forecasts associated with the common shock u are less accurate than those associated with either the AR or the ARDL model specifications. However, there is a number of projections associated with specific variables and obtained using the prediction equation (9) which perform better than the AR and the ARDL also for the Philippines EMP index. The overall forecasting exercise carried in this paper suggest that the Dynamic Factor model has good potential leading indicator properties regarding foreign currency turmoil events.

We now discuss the results in Table 1 regarding the forecasting performance of the different variables included in the dataset. First, we can observe that most of the vulnerability indicators of country i have a good predictive performance of the EMP index in country i (e.g., they have a good "direct" forecasting performance) and of the EMP index in country j (e.g., they are capable to predict cross countries events affecting the EMP index).

[6] To save space we have reported only the KPS scores, and not the various plots of the actual realisation of the EMP indices together with the probability forecasts associated with the different model specifications.

Specifically, from Table 1 we can observe that the ratio of the money aggregate M2 to the stock of international reserves has a good performance in forecasting directly currency turmoil in Malaysia and Korea. This vulnerability indicator also shows to predict successfully cross countries crisis events. In particular, a) the Korean and Thailand M2 ratios lead the EMP in Indonesia; b) the Indonesian, Korean, and Thailand M2 ratios lead the Malaysian crisis event; c) the Indonesia, Malaysia and the Korean M2 ratio lead the Philippines EMP; d) the Malaysian, M2 ratio lead the Korean crisis events; e) the Indonesian, Malaysian and Korean M2 ratios lead Thailand EMP.

From Table 1 another vulnerability indicator such as the ratio of imports to the total stock of international reserves shows a good performance in forecasting directly currency turmoil only in Malaysia and Korea. Furthermore, this indicator is found to be a good predictor especially when forecasting cross country crisis events. In particular, the EMP indices of Malaysia, Philippines and Thailand are accurately predicted by the imports ratios of the other remaining countries.

The results in Table 1 suggest that total (banking) external debt ratio to the stock international reserves shows to be a good predictor directly of the Thailand and Korean currency turmoil. The issues of international bonds (relative to the stock of foreign reserves) of the countries under investigation shows to be a good direct leading indicator only of the Korean EMP index.

The out of sample forecasting results in Table 1 suggest that not only the total size of external debt , but also the constituents of the maturity and geographical composition of foreign debt have good leading indicator properties. In particular the whole maturity composition of Malaysia and Korea, and the short term debt of Philippines are able to correctly predict the currency turmoil events, in Malaysia, Korea and the Philippines, respectively.

As for geographical composition of external debt, we can observe that a) most of the exposure of European countries to Indonesia is quite successful in forecasting the Indonesian currency crisis; most of the European and the Japanese exposure to Malaysia, Korea and Thailand is a good leading indicator of the Malaysian, Korean and Thailand EMP indices, respectively. Finally, the Philippines EMP index is predicted relatively well only when we consider the exposure of European countries and Japan to other four emerging countries of the Asian region under investigation. External borrowing from the US (relative to the stock of foreign reserves) can help to forecast currency turmoil only via spillover effects. In particular, the exposure of US to Thailand, Malaysia, and to the Philippines has a good predictive performance for the Korean EMP.

Finally, from Table 1 we can observe that the whole sector composition of external debt in Malaysia and Korea is capable to predict relatively well the Malaysian and Korean currency turmoil events.

To summarise, we find that not only idiosyncratic country specific variables associated with country i, but also the different vulnerability indicators of country j and a regional vulnerability indicator (with the exception of the Philippines) can help to predict a crisis event in country i. Therefore, the forecasting results suggest that system interdependencies, modelled through the DF model, cannot be ignored when the aim is to predict currency turmoil in a specific country. The projection equations associated with DF models take into account the spillover effects among the different variables given that both the factors and their loadings are obtained from the sample covariance matrix of the dataset x. However, given that predictions from (13) do not perform well, we argue that the system interdependencies per se are not enough to explain the superior performance of the DF model. We also need to take into account the capability of the DF method in filtering out the noise associated with each variable in the dataset x (see Forni et al. 2003)

6 Conclusions

Most of the empirical studies on the predictability of currency crises have been based upon in sample forecasting analysis. The studies of Berg and Pattillo (1999) and Berg et al. (2004a) are an exception. In this paper we are interested in the out of sample predictability of balance of payment crises, using the information conveyed by a large dataset of vulnerability indicators. For this purpose we use the Dynamic Factor model suggested by Stock and Watson (2002) and we use stochastic simulation to produce probability forecasts (out of sample) for the Exchange Market Pressure index of a number of East Asian countries. We find that the Dynamic Factor model (either through shock to a regional vulnerability indicator or though most of the shocks to each single variable in the large dataset considered) improves over a number of benchmark models in terms of forecasting performance.

References

[1] Berg, A. and C. Pattillo, (1999): "Predicting currency crises: the indicators approach and an alternative", *Journal of International Money and Finance*, 18, 561-586.

[2] Berg, A., Borensztein E., and C. Pattillo, (2004): "Assessing Early Warning Systems: How Have They Worked in Practice?", *IMF* working paper 04/052.

[3] Calvo, A. and C.M. Reinhart (1996) "Capital flows to Latin America: is there evidence of contagion effects?" in: G.A. Calvo, M. Goldstein and E. Hochreitter, ed., Private Capital Flows to Emerging Markets. Washington DC: Institute for International Economics.

[4] Calvo, G.A., (1999): "Contagion in emerging markets: when Wall Street is a career", University of Maryland Discussion Paper.

[5] Calvo, G.A. and E. Mendoza, (1999) "Rational contagion and globalisation of securities markets", *Journal of International Economics*, forthcoming.

[6] Chauvet, M. and F. Dong (2004) "Leading Indicators of Country Risk and Currency Crises " The Asian Experience," *Economic Review*, Federal Reserve Bank of Atlanta, First Quarter, Vol. 89, No. 1, 26-37, 2004.

[7] Eichengreen B., A. Rose and C. Wyplosz, (1996), "Contagious currency crises", *Scandinavian Economic Review* 98(4): 463-484.

[8] Forni, M., M. Hallin, M. Lippi, and L. Reichlin, (2000) "The generalised dynamic factor model: identification and estimation". The Review of Economics and Statistics, 82, 540-554.

[9] Forni, M., Lippi, M., Reichlin L. (2003): "Opening the Black Box: structural factor model versus structural VAR models" CEPR discussion paper 4133.

[10] Girton, L. and Roper, D. (1977): "A monetary model of exchange market pressure applied to the postwar Canadian experience", *American Economic Review*, 67, pp. 537-48.

[11] Glick, R. and Rose, K.A (1998) "Contagion and Trade: Explaining the Incidence and Intensity of Currency Crises" NBER Working Paper, no. 6806.

[12] Goldstein, M., Kaminsky G. and Reinhart, C. (2000a): ”Assessing financial vulnerability: an early warning system for emerging markets”, Institute for International Economics.

[13] Goldstein, M, Kaminsky, G. and C. Reinhart (2000b) ”An assessment of vulnerability: out of sample results” in Assessing Financial Vulnerability: An Early Warning System for Emerging Markets, Institute of International Economics

[14] Jacob J., Kuper, G. and Lestano, (2004): ”Currency crises in Asia: a multivariate logit approach”, Department of Economics, University of Groningen, *mimeo*

[15] Kaminsky, G.L., S. Lizondo, and C.M. Reinhart, (1998): ”Leading indicators of currency crises”, *IMF Staff Papers*, 45(1).

[16] Kaminsky, Graciela L. and Carmen M. Reinhart (2000) “On Crises, Contagion, and Confusion.” Journal of International Economics 51: 145-168.

[17] Kaminsky, G.L. and Reinhart, C. (2001): ”Bank Lending and Contagion: Evidence From the Asian Crisis ”, in Regional and Global Capital Flows: Macroeconomic Causes and Consequences; Takatoshi Ito and Anne Krueger, eds.;Chicago: University of Chicago Press for the NBER, 73-99.

[18] Kapetanios, G. and M. Marcellino, (2003),“A Comparison of Estimation Methods for Dynamic Factor Models of Large Dimensions”, Queen Mary, Univeristy of London, WP 489.

[19] Kodres, L.E. and M. Pritsker, (1999): ” A rational expectations model of financial contagion”, FEDS working paper 1998-48, The Federal Reserve Board.

[20] Mody, A. and M. P. Taylor, (2003): “Common vulnerabilities”, *CEPR* discussion paper 3759.

[21] Sbracia, M. and A. Zaghini, (2001): “The role of the banking system in the international transmission of shocks”, Banca d’Italia Discussion Paper, 409.

[22] Schinasi, G. J. and R.T. Smith, (1999): “Portfolio diversification, leverage, and financial contagion”, IMF working paper 99/136.

[23] Stock, J.H. and M.W. Watson, (2001), “Macroeconomic Forecasting Using Diffusion Indexes”, *Journal of Business and Economic Statistics*, 20, 147-62

[24] Tanner, E., (2002) "Exchange market pressure, currency crises, monetary policy: additional evidence from emerging markets", IMF working paper 02/14

[25] Van Rijckegem, C. and B. Weder, (2003): "Spillovers through banking centers: a panel data analysis of bank flows", *Journal of International Money and Finance,* 22, 4, pp. 483-509

[26] Zhuang, J. and M. Dowling (2002) "Causes of the 1997 Finanicial Asian crisis: what can an Early Warning System model tell us?", Asian Development Bank policy brief, no 7.

Data Appendix

1. **Indo_debt_le1y**: Indonesia external debt with maturity up to and including one year
2. **Indo_debt_le2y**: Indonesia external debt with maturity over one year up to two years
3. **Indo_debt_gt2y**: Indonesia external debt with maturity over two years

4. **Indo_debt_banks**: Indonesian banking sector external debt
5. **Indo_deb_publsec**: Indonesian public sector external debt
6. **Indo_deb_nbpriv**: Indonesian non bank private sector external debt
7. **Indo_und_cr**: Indonesia undisbursed credit commitments
8. **Indo_locc**: Indonesia local currency claims
9. **Indo_debt_Bel**: Indonesia bank borrowing from Belgium
10. **Indo_debt_Fra**: Indonesia bank borrowing from France
11. **Indo_debt_Ger:**Indonesia bank borrowing from Germany
12. **Indo_debt_Ita:**Indonesia bank borrowing from Italy
13. **Indo_debt_Jap**: Indonesia bank borrowing from Japan
14. **Indo_debt_Neth**: Indonesia bank borrowing from Netherlands
15. **Indo_debt_Swe**: Indonesia bank borrowing from Sweden
16. **Indo_debt_Swi**: Indonesia bank borrowing from Switzerland
17. **Indo_debt_UK**: Indonesia bank borrowing from UK
18. **Indo_debt_US**: Indonesia bank borrowing from US
19. **Mal_debt_le1y**: Malaysia external debt with maturity up to and including one year
20. **Mal_debt_le2y**: Malaysia external debt with maturity over one year up to two years
21. **Mal_debt_gt2y**: Malaysia external debt with maturity over two years
22. **Mal_debt_banks**: Malaysia banking sector external debt
23. **Mal_deb_publsec**: Malaysia public sector external debt
24. **Mal_deb_nbpriv**: Malays non bank private sector external debt
25. **Mal_und_cr**: Malaysia undisbursed credit commitments
26. **Mal_locc**: Malaysia local currency claims

27. **Mal_debt_Bel**: Malaysia bank borrowing from Belgium
28. **Mal_debt_Fra**: Malaysia bank borrowing from France
29. **Mal_debt_Ger**: Malaysia bank borrowing from Germany
30. **Mal_debt_Italy**: Malaysia bank borrowing from Italy
31. **Mal_debt_Jap**: Malaysia bank borrowing from Japan
32. **Mal_debt_Neth**: Malaysia bank borrowing from Netherlands
33. **Mal_debt_Swe**: Malaysia bank borrowing from Sweden
34. **Mal_debt_Swi**: alaysia bank borrowing from Switzerland
35. **Mal_debt_UK**: Malaysia bank borrowing from UK
36. **Mal_debt_US**: Malaysia bank borrowing from US
37. **Phil_debt_le1y**: Philippines external debt with maturity up to and including one year
38. **Phil_debt_le2y**: Philippines external debt with maturity over one year up to two years
39. **Phil_debt_gt2y**: Philippines external debt with maturity over two years
40. **Phil_debt_banks**: Philippines banking sector external debt
41. **Phil_deb_publsec**: Philippines public sector external debt
42. **Phil_deb_nbpriv**: Philippines non bank private sector external debt
43. **Phil_und_cr**: Philippines undisbursed credit commitments
44. **Phil_locc**: Philippines local currency claims
45. **Phil_debt_Bel**: Philippines bank borrowing from Belgium
46. **Phil_debt_Fra**: Philippines bank borrowing from France
47. **Phil_debt_Ger**: Philippines bank borrowing from Germany
48. **Phil_debt_Ita**: Philippines bank borrowing from Italy
49. **Phil_debt_Jap**: Philippines bank borrowing from Japan
50. **Phil_debt_Neth**: Philippines bank borrowing from Netherlands
51. **Phil_debt_Swe**: Philippines bank borrowing from Sweden
52. **Phil_debt_Swi**: ilippines bank borrowing from Switzerland
53. **Phil_debt_UK:** Philippines bank borrowing from UK
54. **Phil_debt_US**: Philippines bank borrowing from US
55. **Kor_debt_le1y**: Korea external debt with maturity up to and including one year
56. **Kor_debt_le2y**: Korea external debt with maturity over one year up to two years
57. **Kor_debt_gt2y**: Korea external debt with maturity over two years
58. **Kor_debt_banks**: Korea banking sector external debt
59. **Kor_deb_publsec**: Korea public sector external debt
60. **Kor_deb_nbpriv**: Korea non bank private sector external debt
61. **Kor_und_cr**: Korea undisbursed credit commitments
62. **Kor_locc**: Korea local currency claims
63. **Kor_debt_Fra**: Korea bank borrowing from France
64. **Kor_debt_Ger**: Korea bank borrowing from Germany
65. **Kor_debt_Ita**: Korea bank borrowing from Italy

66. **Kor_debt_Jap**: Korea bank borrowing from Japan
67. **Kor_debt_Neth**: Korea bank borrowing from Netherlands
68. **Kor_debt_Swe**: Korea bank borrowing from Sweden
69. **Kor_debt_Swi**: Korea bank borrowing from Switzerland
70. **Kor_debt_UK**: Korea bank borrowing from UK
71. **Kor_debt_US**: Korea bank borrowing from US
72. **Thai_debt_le1y**: Thailand external debt with maturity up to and including one year
73. **Thai_debt_le2y**: Thailand external debt with maturity over one year up to two years
74. **Thai_debt_gt2y**: Thailand external debt with maturity over two years
75. **Thai_debt_banks**: Thailand banking sector external debt
76. **Thai_deb_publsec**: Thailand public sector external debt
77. **Thai_deb_nbpriv**: Thailand non bank private sector external debt
78. **Thai_und_cr**:Thailand undisbursed credit commitments
79. **Thai_locc**: Thailand local currency claims
80. **Thai_debt_Bel**: Thailand bank borrowing from Belgium
81. **Thai_debt_Fra**: Thailand bank borrowing from France
82. **Thai_debt_Ger**: Thailand bank borrowing from Germany
83. **Thai_debt_Ita**: Thailand bank borrowing from Italy
84. **Thai_debt_Jap**: Thailand bank borrowing from Japan
85. **Thai_debt_Neth**: Thailand bank borrowing from Netherlands
86. **Thai_debt_Swe**: Thailand bank borrowing from Sweden
87. **Thai_debt_Swi**: Thailand bank borrowing from Switzerland
88. **Thai_debt_UK**: Thailand bank borrowing from UK
89. **Thai_debt_US**: Thailand bank borrowing from US
90. **Indo_totdebt**: Indonesia total external debt
91. **Mal_totdebt**: Malaysia total external debt
92. **Phil_totdebt**: Philippines total external debt
93. **Kor_totdebt**: Korea total external debt
94. **Thai_totdebt**: Thailand total external debt
95. **Indo_intbond**: Indonesia international bond issues
96. **Mal_intbond**: Malaysia international bond issues
97. **Phil_intbond**: Philippines international bond issues
98. **Kor_intbond**: Korea international bond issues
99. **Thai_intbond**: Thailand international bond issues
100. **Indo_M2**: Indonesia total money supply M2
101. **Mal_M2**: Malaysia total money supply M2
102. **Phil_M2**: Philippines total money supply M2
103. **Kor_M2**: Korea total money supply M2
104. **Thai_M2**: Thailand total money supply M2

105. **Indo_imp**: Indonesia total imports
106. **Mal_imp**: Malaysia total imports
107. **Phil_imp**: Philippines total imports
108. **Kor_imp**: Korea total imports
109. **Thai_imp**: Thailand total imports
110. **Indo_EMP**: Indonesia exchange market pressure
111. **Mal_EMP**: Malaysia exchange market pressure
112. **Phil_EMP**: Philippines exchange market pressure
113. **Kor_EMP**: Korea exchange market pressure
114. **Thai_EMP**: Thailand exchange market pressure

Table 1: KPS scores					
	Indo	Mal	Phil	Kor	Thai
Indo_debt_le1y	0.00	-0.37	-0.58	0.61	-0.11
Indo_debt_le2y	0.00	0.47	0.26	0.28	-0.11
Indo_debt_gt2y	-0.06	0.53	0.32	0.61	-0.17
Indo_debt_banks	-0.56	-0.37	0.68	0.06	-0.22
Indo_deb_publsec	-0.61	0.58	0.53	0.56	-0.17
Indo_deb_nbpriv	0.00	-0.32	-0.53	0.61	0.11
Indo_und_cr	-0.11	-0.47	-0.58	-0.06	-0.06
Indo_locc	0.00	0.63	-0.16	0.11	-0.39
Indo_debt_Bel	0.00	-0.53	-0.47	-0.56	-0.06
Indo_debt_Fra	-0.06	0.58	-0.68	0.61	-0.06
Indo_debt_Ger	0.44	0.84	-0.21	0.39	-0.28
Indo_debt_Ita	-0.28	0.68	-0.32	0.22	0.39
Indo_debt_Jap	0.00	0.58	0.37	0.50	-0.28
Indo_debt_Neth	0.22	-0.05	-0.26	0.28	0.28
Indo_debt_Swe	0.06	0.68	-0.58	0.11	0.28
Indo_debt_Swi	0.39	0.84	-0.21	-0.17	0.33
Indo_debt_UK	0.11	0.68	-0.63	0.39	-0.06
Indo_debt_US	-0.50	-0.37	-0.58	-0.06	-0.17
Mal_debt_le1y	0.11	0.84	-0.37	0.06	-0.11
Mal_debt_le2y	-0.72	0.47	0.42	0.61	-0.11
Mal_debt_gt2y	-0.33	0.42	0.26	0.39	-0.11
Mal_debt_banks	0.28	0.84	0.53	0.78	-0.06
Mal_deb_publsec	-0.28	0.26	0.42	0.17	-0.61
Mal_deb_publsec	0.28	0.84	-0.26	0.39	-0.06
Mal_deb_undcr	0.00	0.58	0.37	0.11	0.06
Mal_deb_locc	0.28	-0.11	0.79	0.28	0.33
Mal_debt_Bel	0.33	0.89	-0.26	0.17	0.44
Mal_debt_Fra	0.06	-0.26	-0.42	0.56	0.22
Mal_debt_Ger	0.39	0.89	-0.05	0.33	0.50
Mal_debt_Ita	-0.56	-0.32	0.84	-0.11	0.28
Mal_debt_Jap	0.28	0.42	0.26	0.17	0.06
Mal_debt_Neth	0.39	0.89	-0.21	0.28	0.50
Mal_debt_Swe	0.28	0.47	0.58	0.06	-0.06
Mal_debt_Swi	-0.06	0.79	0.53	0.44	0.50
Mal_debt_UK	-0.22	-0.16	0.58	0.28	0.44
Mal_debt_US	-0.11	-0.37	-0.68	0.67	0.00
Phil_debt_le1y	0.44	-0.42	-0.42	0.44	0.06

Table 1 (cont.): KPS scores					
	Indo	Mal	Phil	Kor	Thai
Phil_debt_le2y	0.00	-0.63	0.42	0.78	-0.17
Phil_debt_gt2y	0.33	-0.37	-0.26	0.44	-0.39
Phil_debt_banks	0.39	-0.37	-0.47	0.44	0.17
Phil_debt_publsec	0.50	-0.32	-0.37	0.44	-0.44
Phil_deb_nbpriv	0.39	-0.32	-0.32	0.44	0.28
Phil_deb_undcr	0.28	0.68	-0.16	0.44	0.11
Phil_deb_locc	0.39	0.84	-0.16	0.44	-0.06
Phil_deb_Bel	0.39	-0.16	-0.26	0.44	-0.06
Phil_deb_Fra	0.39	-0.42	-0.47	0.39	0.06
Phil_deb_Ger	0.44	0.89	-0.05	0.44	-0.06
Phil_deb_Ita	0.44	0.63	0.47	0.39	0.11
Phil_deb_Jap	0.33	-0.42	-0.32	0.44	-0.44
Phil_deb_Neth	0.28	0.84	-0.16	0.50	0.50
Phil_deb_Swe	0.39	0.68	-0.21	0.39	0.39
Phil_deb_Swi	0.28	0.68	-0.16	0.94	0.33
Phil_deb_UK	0.44	-0.32	0.68	0.44	-0.44
Phil_deb_US	0.44	-0.37	-0.32	0.44	-0.44
Kor_debt_le1y	0.11	-0.53	-0.21	0.17	-0.17
Kor_debt_le2y	-0.11	0.84	-0.16	0.50	0.22
Kor_debt_gt2y	0.00	0.58	-0.11	0.22	0.17
Kor_debt_banks	0.28	-0.42	-0.16	0.33	0.00
Kor_debt_publsec	0.00	0.68	-0.11	0.28	0.39
Kor_debt_nbpriv	0.22	-0.47	-0.11	0.28	0.00
Kor_debt_undcr	0.17	0.37	-0.16	0.06	-0.17
Kor_debt_locc	0.17	0.63	-0.16	0.78	-0.50
Kor_debt_Bel	0.11	-0.53	-0.11	0.17	0.28
Kor_debt_Fra	0.28	-0.37	-0.11	0.89	0.00
Kor_debt_Ger	-0.28	-0.26	0.63	0.22	0.17
Kor_debt_Ita	0.33	0.53	-0.11	-0.22	0.06
Kor_debt_Jap	0.17	0.74	-0.05	0.22	0.28
Kor_debt_Neth	0.50	-0.26	0.84	0.44	0.17
Kor_debt_Swe	0.22	-0.26	0.95	0.28	0.44
Kor_debt_Swi	-0.44	0.95	-0.11	0.06	0.50
Kor_debt_UK	-0.06	0.63	-0.16	0.61	0.00
Kor_debt_US	-0.17	0.47	-0.26	0.00	-0.11
Thai_debt_le1y	-0.17	-0.37	0.47	0.39	-0.06

Table 1 (cont.): KPS scores					
	Indo	Mal	Phil	Kor	Thai
Thai_debt_le2y	-0.50	0.63	0.79	0.61	-0.44
Thai_debt_gt2y	0.22	0.47	-0.21	0.22	0.00
Thai_debt_bank	-0.22	-0.42	-0.47	0.33	0.06
Thai_debt_publsec	0.33	0.53	-0.16	0.11	-0.61
Thai_debt_nbpriv	-0.28	-0.32	0.79	0.22	0.11
Thai_debt_undcr	-0.33	-0.63	-0.42	0.17	-0.67
Thai_debt_locc	0.17	0.84	-0.16	0.11	0.39
Thai_debt_Bel	0.50	0.68	0.47	0.39	0.06
Thai_debt_Fra	0.33	0.68	-0.42	0.28	0.17
Thai_debt_Ger	-0.11	0.68	-0.11	0.33	-0.06
Thai_debt_Ita	-0.06	0.84	0.58	0.33	0.50
Thai_debt_Jap	-0.17	-0.53	0.58	0.22	0.11
Thai_debt_Neth	-0.17	0.53	-0.42	0.33	-0.11
Thai_debt_Swe	0.33	0.47	-0.53	0.44	0.06
Thai_debt_Swi	-0.50	0.53	0.42	0.67	-0.50
Thai_debt_UK	0.33	0.84	-0.26	0.33	-0.11
Thai_debt_US	0.39	-0.42	-0.53	0.33	-0.11
Indo_totdebt	0.00	-0.37	-0.58	0.61	-0.56
Mal_totdebt	0.11	-0.21	-0.32	0.33	0.44
Phil_totdebt	0.39	-0.37	-0.32	0.44	-0.44
Kor_totdebt	0.22	0.47	-0.26	0.28	-0.17
Thai_totdebt	-0.22	-0.42	0.42	0.28	0.17
Indo_intbond	-0.44	-0.37	0.37	0.56	-0.11
Mal_intbond	0.11	-0.42	0.47	0.22	0.28
Phil_intbond	-0.22	0.63	-0.16	0.39	0.39
Kor_intbond	-0.44	-0.32	0.89	0.61	0.00
Thai_intbond	-0.28	-0.37	0.53	0.11	0.00
Indo_M2	0.00	-0.47	-0.42	0.33	0.17
Mal_M2	0.11	0.84	-0.21	0.17	0.44
Phil_M2	0.33	0.53	-0.11	0.44	-0.44
Kor_M2	-0.06	0.53	-0.16	0.50	-0.67
Thai_M2	-0.56	0.53	0.32	0.39	-0.11
Indo_imp	-0.17	-0.47	-0.63	0.28	-0.17
Mal_imp	0.06	0.89	-0.11	0.22	0.44
Phil_imp	0.28	0.68	-0.11	0.44	0.33
Kor_imp	-0.06	0.58	-0.16	0.50	-0.22
Thai_imp	0.33	-0.58	0.21	0.83	-0.61