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Forecasting Financial Crises and Contagion in Asia using Dynamic Factor Analysis

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May 25, 2008

Abstract

In this paper we use principal components analysis to obtain vulnerability indicators able to predict financial turmoil. Probit modelling through principal components and also stochastic simulation of a Dynamic Factor model are 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 principal components model improves upon a number of competing models, in terms of out-of-sample forecasting performance.

Keywords: Financial Contagion, Dynamic Factor Model
JEL code: C32,C51,F34

1 Introduction

The 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 fueled a new variety of theories, also known as third generation of currency crisis models, 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. Work

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based on third generation of currency crisis models has motivated various reports 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", published in 2000 stresses the importance, for Central Banks, of holding foreign reserves 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 System literature (EWS).

Currency turbulence in this paper is proxied by using the Exchange Market Pressure Index (EMP). This index was first used by Girton and Roper (1977), and subsequently by a number of authors in the context of exchange rate crises (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 (i.e., 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.

There are two main methods used in the EWS literature to predict currency market turbulence. One method relies on the signal approach proposed by Kaminsky et al. (1998a), and the other one relies on "parametric" modelling, given that it is based upon limited dependent variable regression modelling (see the study of Frankel and Rose, 1996, among the others). The EWS modelling approach we follow in this paper is the "parametric" one, and it is based upon the investigation of the out-of-sample predictive performance of a composite leading indicator via regression analysis. In particular, the composite indicator is constructed by extracting common factors from the Bank for International Settlements, BIS, dataset which gives detailed information on the composition of external debt. To our knowledge this dataset has not been previously exploited to construct composite leading indicator of a currency crisis event, defined in terms of the EMP index[1]. The choice of using

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[1]The use of annual data by Frenkel and Rose (1996) allows to exploit information on the composition of

disaggregated data on external debt is based upon the suggestion given by various 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. Given that BIS external debt data are available for a relatively long data span (starting from 1983) only at low frequency (bi-annual basis), the number of cross sections exceed the time series observations, hence it is not practical to use standard state space model methods to extract factors (especially, when one is interested in recursive estimation in order to produce out-of-sample predictions for the forecast evaluation period). Therefore, we use factors extraction based on principal components analysis as suggested by Stock and Watson (2002)[2]. Furthermore, contrary to previous studies which have only explored the out-of-sample forecasting performance of the composite indicator, we also assess which group of variables (say, short term debt) play an important role in predicting out-of-sample the crisis event through the composite leading indicator. The use of principal components for the purpose of constructing leading indicators of currency crisis has already been put forward by Cipollini and Kapetanios (2003) who produce out-of-sample point forecast of the EMP index in East Asian countries for the 1997-1998 period, and also by Inoue and Rossi (2006) and by Jacobs et al. (2008). While the probability forecast of currency crisis events in the study of Inoue and Rossi (2006) rely on modelling the conditional second moments of the nominal exchange rate through principal components, the probability forecasts we produce are obtained by modelling the conditional first moment of the EMP index through common factors[3]. As for the out-of-sample probability forecasts, Jacobs et al. (2008) focus only on one year, 2002, (where there is no evidence of particular turbulence in the East Asian currency markets) and there is no comparison with forecasts produced by other benchmark models, including an AR for the EMP. In this paper, we produce out-of-sample probability forecasts, first, by employing probit modelling (which is standard when using the parametric approach to EWS). Second, we also use stochastic simulation of the Dynamic Factor model, (DF), following the suggestion of Forni et al. (2005) on how to retrieve a single common shock which we interpret as a regional vulnerability indicator. The probability forecast accuracy is assessed by using both the Kuipers Score and the Matthews correlation coefficient.

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external debt. However, Frenkel and Rose (1996) focus on predicting large nominal exchange rate depreciations and not crisis events defined in terms of the EMP index.

[2]The Stock and Watson (2002) method is a time-domain based approach. In Forni, et al, (2000) the factor extraction is obtained using an a frequency domain based approach. Finally, Kapetanios and Marcellino (2003) use an approach based upon a state space model.

[3]Inoue and Rossi (2006) probability forecasts are for crisis events defined in terms of nominal exchange rate depreciations bigger than 20%. We argue that this type of currency crisis considered does not include speculative attacks successfully warded off by the authorities through reserve sales

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

2   Background literature

As already mentioned in the Introduction, the first method used in the EWS literature is the signal approach proposed by Kaminsky et al. (1998a) 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). Kaminsky (1998b) and Goldstein et al. (2000) base their prediction of a crisis occurring in a specific country by monitoring the evolution not only of a single macro-indicators, but also on a composite leading indicator, which aggregates different macro-variables, with weights given by inverse of the noise to signal ratio. Goldstein et al. (2000) 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 and it can be argued that they can be motivated by the existing theoretical studies on financial contagion. In particular, Kodres and Pritsker (1998) also present a model with rational agents and information asymmetries, where financial investors are engaged in cross market hedging. Furthermore, Calvo and Mendoza (2000) present a model where the fixed costs of gathering and processing country-specific information give rise to herding behavior, even when investors are rational. Calvo (1999) stresses 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.

The alternative method in the EWS literature is to use limited dependent variable regression models to estimate the probability of a currency crisis. The currency crisis indicator is modeled as a zero-one variable, as in the signal approach, and the prediction of the model is interpreted as the probability of a crisis. More specifically, in line with the probit regression analysis put forward by Frenkel and Rose (1996), Berg et al. (1999) use this model

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specification with the explanatory variables measured in percentile terms. Also, the private sector models developed by Credit Suisse First Boston, Goldman Sachs and Deutsche Bank use logit regressions. The study of Van Rijckeghem and Weder (2003) uses probit regression to examine the role of a common lender channel in triggering crisis events. The authors (op. cit.) rely on disaggregate data on external debt produced by the BIS to construct measures of competition for fund in order to explore the role played by a common lender channel.

While the previous studies (with the exception of Goldstein et al., 2000) are based upon in sample prediction, the studies of Berg and Pattillo (1999) and of Berg et al. (2004) show that the out-of-sample forecasts of East Asian 1997-1998 currency crisis events produced through the signal approach are fairly good, with many of the most vulnerable countries in fact being the hardest hit in terms of crisis severity. In Berg et al. (2004) the out of sample forecasting performance for the post East Asian crisis period is also assessed and the signal approach is found to perform better than the regression based approach. The short-horizon private sector models developed by Credit Suisse First Boston, Goldman Sachs and Deutsche Bank are shown to have a poor out of sample predictive performance. The study of Fuertes and Kalotychou (2006a) concentrates on several logit model specifications (with different degree of unobserved heterogeneity) which are found to be less successful, in terms of out-of-sample forecasting performance of sovereign default crisis, than a pooled logit model. Further, Fuertes and Kalotychou (2006b) consider not only logit regression but also a non parametric method based upon K-means clustering to predict crisis events. Fuertes and Kalotychou (2006b) find that a combination of forecasts from the different methods generally outperform both the individual and naive forecasts. The empirical analysis reveals that the best combining scheme depends also on the decision-makers preferences regarding the desired trade-off between missed defaults and false alarms (see also the study of Bussiere and Fratzscher, 2002, on the issue of designing the features of their EWS model according to the preferences and to the degree of risk-aversion of policymakers).

Finally, there are studies that have constructed composite leading indicators of currency crisis events using diffusion indices rather than the weighting scheme suggested by Kaminsky (1998b) and by Goldstein et al. (2000). Beyond the studies which rely upon the construction of diffusion indices using principal component analysis fitted to a large dataset (see the studies of Cipollini and Kapetanios, 2003; Inoue and Rossi, 2006; Jacobs et al., 2008) there are few studies which extract common factors from small datasets. Mody and Taylor (2003) use Kalman filter estimation of state space models in order to extract a measure of regional vulnerability in a number of emerging market countries, and, in order to produce in sample

prediction of the currency market turbulence. Another diffusion index is the one constructed by Chauvet and Dong (2004) who develop a factor model with Markov regime switching dynamics in order to produce in sample and out-of-sample prediction of nominal exchange rates in a number of the East Asian countries.

3 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, first, how the DF model can be used to predict currency crisis events by building a vulnerability indicator common to the whole East Asian region. We will also assess the contribution of group of variables to the DF model performance in forecasting the EMP index. Finally we will describe how to obtain probability forecasts using different competing models.

3.1 Model specification for a large dataset

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

$$x_t = \Gamma f_t + \xi_t \tag{1}$$

where x_t is an $n \times 1$ vector of (stationary) variables observed at time t; f_t is an r dimensional vector of factors (latent variables), with r much smaller than n; Γ is an $n \times r$ matrix of factor loadings and ξ_t is an $n \times 1$ idiosyncratic shock component. In the first stage of the analysis, each series is de-meaned and divided by the corresponding sample standard deviation. The set of common factors f_t and the idiosyncratic component ξ_t (treated as iid in this study) are assumed to be orthogonal to each other. Then, we apply principal component analysis to the standardised $T \times n$ panel x_t. The factor 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. The use of estimated factors instead of true ones in futher econometric analysis may pose a generated regressor problem. However, as long at n is sufficiently large compared to T this is not an issue. In particular, Bai (2003) has shown that, when estimated factors are used in a regression context, no generated regressor problem arises,as long as $\sqrt{T}/n \to 0$.

Following Forni et al. (2005), the dynamics of the factors are described by:

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

where D is the $r \times r$ autoregressive coefficient matrix and ε_t is an $r \times 1$ vector of (reduced form) innovations. The coefficient matrix D and the residuals ε_t of the VAR(1) model in (**??**) 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, ε_t, in **??**):

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

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

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

From equations (**??**) and (**??**) 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 **??**).

3.2 Density forecast from the principal components model

In this section we describe how we obtain the density forecasts of the EMP index associated, with the unobservable common shock u_t (interpreted as a regional vulnerability indicator). 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 of the j-th country:

$$EMP_{j,t+1} = a_0 + \sum_{k=1}^{p} \alpha_k EMP_{i,t+1-k} + \sum_{i=1}^{r} \beta_i \hat{f}^e_{i,t+1} + \nu_{j,t+1} \tag{5}$$

In this model, $\hat{f}^e_{i,t+1}$ is the one step ahead prediction for the ith component of the r dimensional vector of factors, given by $D_i \hat{f}_t$, where D_i is the i-th row of D and $\hat{f}_t$ is the last

observation (in sample) for the the vector of r estimated factors. In particular, the loading of each factor into the unstandardised EMP_i index is captured by the 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 $\nu_{j,t+1}$ is the idiosyncratic country specific shock for the j-th country.

In order to estimate the coefficients in equation (**??**) 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 the Bayesian information criterion (BIC), as suggested by Stock and Watson, (2002). We obtain the factor estimates and the estimates for the coefficient matrices D and R, following the procedure described in section 3.1. The coefficient estimates for a_0, α_k, $k = 1, ..., p$, and β_i are obtained by regressing (via OLS) the unstandardised EMP index on an intercept, its lags, and on the estimated factors.

In order to produce density forecasts we use Monte Carlo stochastic simulation. Each stochastic simulation replication is given by a combination of the replications of the common (which is, then, interpreted as the regional vulnerability indicator) and idiosyncratic shocks, u_t and $\nu_{j,t}$, respectively. In particular, the s-th replication (scenario) for $EMP_{i,t+1}$, denoted by $EMP_{i,t+1}^s$ is given by

$$EMP_{j,t+1}^s = \left[a_0 + \sum_{k=1}^p \alpha_k EMP_{i,t+1-k} + \sum_{i=1}^r \beta_i \left(D_i \hat{f}_t + R_i u_{t+1}^s \right) \right] + \nu_{j,t+1}^s \qquad (6)$$

where R_i is the i-th row of R and u_{t+1}^s and $\nu_{j,t+1}^s$ denote the s-th replication for u_{t+1} and $\nu_{j,t+1}$, respectively. Both shocks are obtained from draws from standardised Gaussian random variables. The number of replications (hence the number of different scenarios) is 10000 and this is considered as an exhaustive number of scenarios (therefore reducing the computational intensity of the Monte Carlo experiment) if we fix q to unity.

3.3 Density forecasts from competing models

The density forecasts associated with various competitor models are given below:

1. The first model we consider is a naive predictor given by:

$$EMP_{j,t+1}^{naive} = \mu_j + \sigma_j \nu_{j,t+1} \qquad (7)$$

where μ_j and σ_j are the sample mean and the sample standard deviation of the EMP index of country j and $\nu_{j,t+1}$ are realisation of shocks to the EMP index and they are obtained through 10000 draws from a standardised Gaussian distribution.

2. The second model is an optimal AR, which gives the following projection:

$$EMP^{AR}_{j,t+1} = \sum_{k=1}^{p} \alpha_k EMP^{AR}_{j,t+1-k} + \sigma_j \nu_{j,t+1} \tag{8}$$

where the lag order p for the AR model specification is obtained through BIC. The maximum order for the lags of the dependent variable, when using the BIC criterion, has been fixed to four. We estimate σ_j using the standard deviation of the OLS residuals from the estimation of the AR model. The scenarios associated with (**??**) are obtained through 10000 draws from a standardised Gaussian distribution of the idiosyncratic shock $\nu_{j,t+1}$.

3. The third class of models is given by an Autoregressive Distributed Lag model, $ARDL$:

$$EMP^{ARDL}_{i,t+1} = \sum_{k_1=1}^{K_1} \alpha_{k_1} EMP_{i,t+1-k_1} + \sum_{k_2=1}^{K_2} \alpha_{k_2} exog_{j,t+1-k_2} + \sigma_j \nu_{i,t+1} \tag{9}$$

where the lag orders K_1 and K_2 are selected using recursive BIC (fixing the maximum lag order to 4); $exog_j$ is the jth variable entering in the dataset x. The projection equation (**??**) allows to assess whether current and past values of $exog_j$ improves upon the AR, in terms of forecasting performance. The coefficients α_{k_1} and α_{k_2} are estimated by recursive OLS, and the lag orders K_1 and K_2 are retrieved using the BIC criterion. We estimate σ_j using the standard deviation of the OLS residuals from the estimation of the ARDL model. The scenarios associated with (**??**) are obtained through 10000 draws from a standardised Gaussian distribution of the idiosyncratic shocks ν_j[4].

It is important to observe that results either for the ARDL model specification with principal components as regressors or for the models considered in this section would not change if the Monte Carlo experiment is based upon draws from a Student t distribution with k degrees of freedom[5]. 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.

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[4]We have also treated $exog_j$ as stochastic when carrying the simulation experiment. This has been done by adding to the last observation available at time t, that is $exog_{jt}$, the realisation of a standard Gaussian shock multiplied by its standard deviation. The latter is given by the sample standard deviation (using the sample of observations ending at time t) of the jth variable in the dataset x. However, the empirical results do not change.

[5]The associated with draws from Student t distribution with 3, 5, 10 degrees of freedom are available upon request.

3.4   Probit model

We also use the principal components as regressors of a Probit model which is estimated by maximising the log-likelihood:

$$\ln L = \sum_{t=1}^{T} \left\{ \ln \left[\Phi \left(\sum_{j=1}^{r} \gamma_j f_{jt} \right) \right] I(.) + \ln \left[1 - \Phi \left(\sum_{j=1}^{r} \gamma_j f_{jt} \right) \right] [1 - I(.)] \right\} \qquad (10)$$

where $I(.)$ is an indicator function taking value 1 when a crisis event is observed (e.g. when the EMP index at time $t+1$ exceeds a threshold), Φ is the cumulative Gaussian distribution function and the γ's are coefficients to be estimated by using Maximum Likelihood, ML. The number of factors is selected by the one associated with the highest maximised log-likelihood value. The estimates for γ_i are then used to produce probability forecasts as discussed in the next subsection

3.5   Out-of-sample probability forecast and forecast accuracy evaluation

In this section we describe how to obtain probability forecasts from the density forecast of EMP produced by the ARDL model and the competing model or from the estimated Probit model. The crisis events are defined by the observations of the EMP index taking values of either 1.5 standard or two standard deviation above the mean. When 1.5 standard deviations are used as the threshold, the realisations of the EMP index which suggest a crisis event are: a) semesters 1998:1 and 1998:2 for Indonesia; b) semester 1998:1 for Malaysia and for the Philippines; c) semesters 1998:1 and 2001:2 for Korea; d) semesters 1997:2 and 1998:2 for Thailand. When two standard deviations are used as the threshold, the realisations of the EMP index which suggest a crisis event are: a) semesters 1998:1 and 1998:2 for Indonesia and b) semester 1998:1 for Malaysia, Philippines, Korea, and Thailand.We now describe how to obtain the probability forecasts.

We consider as a forecast evaluation period the one given by the last 20 periods (i.e.,. 10 years) in the sample. This is the period 1994:2 to 2004:1. It is important to observe that the coefficient estimates for the model specifications given by equations (??),(??), (??), (??) are obtained using recursive OLS, so as to avoid using future information in the forecasting exercise. In particular, we use data available up to and including the first semester of 1994 and we use the estimated model to produce the second semester of 1994 probability forecast. Then we add to the previous sample the information corresponding to the second semester of 1994, re-estimate the model and we produce the first semester of 1995 probability forecast.

This is repeated throughout the sample, moving ahead one semester, and it gives a forecast evaluation period equal to 20 observations.

Furthermore, for each new sample (which increases by one observation in each iteration) the model specification (e.g. number of lags, and, or of principal components) is selected through BIC. When using stochastic simulation to produce probability forecasts, for each of the 20 periods, we carry Monte Carlo stochastic simulation of the ARDL model specification described in (**??**) in order to generate the alternative scenarios corresponding to the 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 a specific threshold. The resulting number is then divided by the total number of scenarios (e.g. 10000). The probability forecast obtained via Probit modelling are simply given by computing $\Phi\left(\sum_{j=1}^{r} \hat{\gamma}_i f_{i,t}\right)$ where Φ is the cumulative Gaussian distribution function and the $\hat{\gamma}_i$s are the coefficients estimated by maximising the log-likelihood given in (**??**).

In order to evaluate the accuracy of the probability forecasts, we employ the Kuipers Score (see 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 signals a 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, $FA = false\ alarms/(false\ alarms + correct\ rejections)$:

$$KS = H - FA \tag{11}$$

Positive values for the KS scores imply that, at least, one crisis event is correctly signalled and that the model generates proportionally more hits than false alarms. We also use, for the purpose of evaluation the accuracy of probability forecasts, the Matthews (1975) correlation coefficient which is widely applied in biology:

$$MC = \frac{(hits * correct rejections - false alarms * misses)}{\sqrt{\begin{array}{c}(hits + false alarms) * (hits + misses)* \\ (correct rejections + false alarms) * (correct rejection + misses)\end{array}}} \quad (12)$$

This indicator, which is bounded between -1 and +1, has the natural interpretation of the Pearson correlation coefficient between the predicted and realised binary outcomes (see Baldi et al., 2000, for a formal proof). Both the KS and the Matthews correlation coefficient combine all the information contained in the contingency table above in a single value. Zero values for the KS and the Matthews correlation coefficient correspond to the performance of a naive predictor. Therefore, positive values for both the indicators are an indication of an improvement, in terms of forecasting performance, upon a naive predictor.

4 Empirical analysis

4.1 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 a bi-annual basis from 1983:2 to 2004:1 in millions of US dollars, for a total of 42 time series observations[6]. 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, Netherlands, Sweden, Switzerland, the 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 and over two years.

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

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 the US dollar. Each money based indicator of reserves provides 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 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 rate (measured as unit of domestic currency per US dollar), and of the change in the stock of US dollar denominated official reserves (minus gold) scaled by the previous period base money (converted in US dollars). The weights are given by the inverse of the corresponding sample standard deviations.

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 gives a total of 114 variable constituents for the dataset under investigation.

4.2   Empirical Results

The out-of-sample probability forecast are obtained through either recursive OLS or, in the case of Probit modelling, recursive ML estimation. First, we do not report the forecasting results associated with the models given by either a naive predictor, described in eq. (**??**),or by the competing models described in equations (**??**), (**??**), given that the corresponding KS

scores or the Matthew correlation coefficients 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. In the rows labelled ARDL_pc and Probit_pc of Table 1 we report the probability forecast performance (the KS scores are on the left hand side of every table cell and the Matthews correlation coefficient are on the right hand side of every table cell) corresponding with the predictions obtained using recursive OLS and ML estimation, respectively, when using the principal components as regressors. More specifically, in Table 1, we provide results related to forecasting a crisis event defined as 1.5 standard deviation above the mean. In Table 2 we report the probability forecast performance (associated to the models already described for Table 1) of a crisis event defined as two standard deviation above the mean. As we can observe from Tables 1 and 2, for most of the countries, both the KS scores and the Matthews correlation coefficients are positive. This suggests that the use of either a single composite leading indicator, modelled as a common shock, u_t, underlying the dynamics of the observables entering in the large dataset from which we extract the principal components, or the direct use of the principal components in Probit regression gives accurate forecasting results. The only exception, as suggested by Table 1 and 2, is the EMP index for the Philippines, although, as shown in Table 2, the use of a probit model specification with the common factors as regressors, gives a proportion of correct signals exceeding the proportion of false alarms regarding a crisis event in terms of two standard deviation above the EMP sample mean. These results are in line with the probability forecast (over a 6 months horizon) performance of the models studied by Inoue and Rossi (2006) to monitor nominal currency changes in East Asia. The authors (op. cit.) show that diffusion index based probability forecasts are more accurate than other competing models (except for South Korea). Furthermore, our forecast horizon (six months) are comparable with those of private sector models (which are at one and three months horizons) for which a poor out-of-sample forecasting performance (regarding the period pre and post Asian crisis) has been shown by Berg et al. (2004).

Moreover, we argue that it is also interesting to assess the contribution of different set of observable to overall forecasting performance of the Dynamic Factor model. For this purpose, we remove a group of variables, for instance, the short term debt ratio of the stock of international reserves in the five countries, from the large dataset x, and we apply again the DF methodology. We then compare the forecasting performance of the new DF model with the one associated with the whole dataset. More specifically, we are interested in assessing whether and to what extent the new DF model forecasting performance is lower than the one corresponding with diffusion indices obtained by using the whole sample of observations. In

Tables 3 to 8 we report the probability forecast performance of an ARDL model which uses as regressors principal components extracted from a dataset which lacks a specific group of variables and we check whether and to what extent the probability forecast performance of this new model is worse than the one corresponding to diffusion indices obtained by using the whole dataset.

First, we can observe from Table 3 that the probability forecast performance associated with an ARDL model with principal components obtained from a dataset excluding the total size of external debt is not altered. Therefore, we conclude that the total size of debt itself does not play an important role in explaining (out-of-sample) the EMP in each country. However, the maturity and the geographical composition of external debt seem to play an important role. In particular, given that a great deal of attention has been devoted to the common lender channel, we examine whether, by removing the external borrowing either from Europe, or from the US, or from Japan, alters substantially the probability forecast performance of a principal components model. The common lender channel can be justified on the grounds that 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 effects can also operate through the value of collateral (e.g. stocks or government bonds) provided by borrowers. In particular, one can consider a country that is economically open but it has an underdeveloped bank based financial market. If this country has difficulties in backing its funding by asset holdings in a neighbouring country, then the lender (a developed country) will downgrade the borrower (the emerging market) and reduce the amount of credit issued, and this will spread the crisis internationally. Therefore, when a crisis hits the "collateral" economy, the lender will require a sounder backing of its claims. Given the considerable poor probability forecast performance, shown from Table 6 to 8, of a model with principal components extracted from a dataset which lacks this information, especially on external borrowing from Europe, we can conclude that the exposure of European banks towards East Asia has an important role in explaining (out-of-sample) currency turbulence in East Asia. Furthermore, while the contribution of external borrowing from the US seem to be important only for the Malaysian EMP index forecast, the contribution of external borrowing from Japan seems to be important only for the Korean EMP index forecast. These results confirm (on the basis of out-of-sample predictions) the importance of the common lender channel as highlighted in the studies of Van Rijckeghem and Weder (1999) and (2003), Kaminsky and Reinhart (2000) and (2001). From Table 4 and 5 we can infer the important role played by short term external debt relative to long term debt when the focus

is on crisis event defined in terms of 1.5 standard deviation. However, the short term debt seems to be more important than long term debt only for Indonesia and Thailand when the focus is on crisis events defined in terms of two standard deviations. As argued by Chang and Velasco (1999) among the others, 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. Finally, from Table 9, we can also infer the important role played by the ratio of M_2 to the stock of international reserves (used to proxy the potential for resident-based capital flight from the currency) in predicting out-of-sample currency crisis events. These results are in line with the results of Berg and Pattillo (1999) which show the high information content of this particular indicator both in terms of in sample and out of sample forecasting performance.

5   Conclusions

In this paper we are interested in the out-of-sample predictability of balance of payment crises in a number of East Asian countries. The currency turbulence is proxied by the EMP index exceeding a given threshold. For this purpose we construct diffusion indices summarising the information conveyed by external debt disaggregate data from the BIS using principal components. Compared to a number of competing models, diffusion indices forecasts obtained either through Probit modelling or through stochastic simulation of a Dynamic Factor model (see, Stock and Watson, 2002, and Forni et al., 2005), provide superior probability forecast performance. We also find that groups of variables, such as the ratio of external borrowing from European countries to international reserves, or the ratio of the money supply aggregate M_2, to the stock of international reserves play an important role in explaining out-of-sample the dynamics of the EMP index. Finally, we argue that superior probability forecast performance of the principal components model relative to competing models can be explained by recognising the capability of the principal component analysis in filtering out the noise associated with each variable in the dataset x.

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Table 1: Probability Forecasts of a crisis event (1.5 std)					
	Indo	Mal	Phil	Kor	Thai
ARDL_pc	0.44;0.44	0.89;0.54	-0.05;-0.05	0.44;0.44	0.44;0.44
Probit_pc	0.05;NA	0.10;0.07	0.00;NA	0.11;0.11	0.11;0.11

Note: The numbers corresponding the row labelled ARDL_pc are indicators of probability forecast performance (of a crisis event defined as 1.5 standard deviation above the mean) when using the ARDL model, with the principal components as exogenous regressors. The numbers corresponding the row labelled Probit_pc are indicators of probability forecast performance when using the Probit model (estimated by ML), with the principal components as exogenous regressors. In each cell, the number preceding the semicolon is the KS score, whereas the number right after the semicolon in each cell is the Matthews correlation coefficient. NA stands for Not Available and it is due to values both equal to zero for the numerator and the denominator of theMatthews correlation coefficient.

Table 2: Probability Forecasts of a crisis event (2 std)					
	Indo	Mal	Phil	Kor	Thai
ARDL_pc	0.50;0.68	0.89;0.54	-0.05;-0.05	0.94;0.68	0.94;0.68
Probit_pc	0.11;0.11	0.10;0.07	0.10;0.07	0.10;0.07	0.10;0.07

Note: See Note to Table 1. The crisis event is defined as two standard deviation above the mean

Table 3: The role of total debt					
	Indo	Mal	Phil	Kor	Thai
crisis(1.5 std)	0.44;0.44	0.94;0.68	-0.05;-0.05	0.44;0.44	0.44;0.44
crisis(2 std)	0.50;0.68	0.94;0.68	-0.05;-0.05	0.94;0.68	0.94;0.68

Note: In this Table we report indicators of probability forecast performance (the KS score and the Matthews correlation coefficient on the l.h.s. and r.h.s of each cell, respectively) associated with the ARDL model which uses the principal components as exogenous regressors. The principal components have been extracted from a dataset without the ratio of total external debt to the stock of international reserves in each country.

Table 4: The role of short term debt					
	Indo	Mal	Phil	Kor	Thai
crisis(1.5 std)	0.44;0.44	-0.10;-0.07	-0.05;-0.05	-0.05;-0.07	0.44;0.44
crisis(2 std)	0.44;0.44	-0.05;-0.05	-0.05;-0.05	-0.05;-0.05	-0.05;-0.05

Note: see Note to Table 3. The principal components have been extracted from a dataset without the ratio of short term external debt to the stock of international reserves in each country

Table 5: The role of long term debt					
	Indo	Mal	Phil	Kor	Thai
crisis(1.5 std)	0.44;0.44	0.94;0.68	-0.05;-0.05	0.44;0.44	0.44;0.44
crisis(2 std)	0.50;0.68	-0.05;-0.05	-0.05;-0.05	-0.05;-0.05	0.94;0.68

Note: see Note to Table 3. The principal components have been extracted from a dataset without the ratio of long term external debt to the stock of international reserves in each country

Table 6: The role of external borrowing from Europe					
	Indo	Mal	Phil	Kor	Thai
crisis(1.5 std)	-0.05;-0.07	-0.05;-0.05	-0.05;-0.05	-0.05;-0.07	-0.05;-0.07
crisis (2 std)	-0.05;-0.07	-0.05;-0.05	-0.05;-0.05	-0.05;-0.05	-0.05;-0.05

Note: see Note to Table 3. The principal components have been extracted from a dataset without the ratio of external borrowing from Europe to the stock of international reserves in each country

Table 7: The role of external borrowing from the US					
	Indo	Mal	Phil	Kor	Thai
crisis(1.5 std)	0.44;0.44	0.89;0.54	-0.05;-0.05	0.44;0.44	0.44;0.44
crisis (2 std)	0.50;0.68	-0.10;-0.07	-0.05;-0.05	0.94;0.68	0.94;0.68

Note: see Note to Table 3. The principal components have been extracted from a dataset without the ratio of external borrowing from the US to the stock of international reserves in each country

Table 8: The role of external borrowing from Japan					
	Indo	Mal	Phil	Kor	Thai
crisis(1.5 std)	0.44;0.44	0.89;0.54	-0.05;-0.05	0.44;0.44	0.44;0.44
crisis (2 std)	0.50;0.68	0.89;0.54	-0.05;-0.05	-0.05;-0.05	0.94;0.68

Note: see Note to Table 3. The principal components have been extracted from a dataset without the ratio of external borrowing from Japan to the stock of international reserves in each country

Table 9: The role of M_2					
	Indo	Mal	Phil	Kor	Thai
crisis(1.5 std)	-0.05;-0.07	-0.05;-0.05	-0.05;-0.05	0.44;0.44	0.44;0.44
crisis (2 std)	-0.05;-0.07	-0.05;-0.05	-0.05;-0.05	0.94;0.68	0.94;0.68

Note: see Note to Table 3. The principal components have been extracted from a dataset without the external borrowing from the M_2 ratio to the stock of international reserves in each country

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