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Abstract

In this paper we compare the performance of a regional indicator of vulnerability in predicting, out of sample, the crisis events affecting the South East Asian region during the 1997-98 period. A Dynamic Factor method was used to retrieve the vulnerability indicator and stochastic simulation is used to produce probability forecasts. The empirical findings suggest evidence of financial contagion.

Keywords: Financial Contagion, Dynamic Factor Model

JEL code: C32, C51, F34

1 Introduction

The recent currency and financial turmoil affecting the Latin American countries during the 1994 period and the East Asian emerging market economies

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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 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 to total stock of external debt to stock of international reserve or the short term external debt ratio to 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.

As described in Section 2, 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. Specifically, we employ a Dynamic Factor model, DF, and we pool

the large number of balance sheet data for the countries under investigation to estimate a common shock interpreted as a regional vulnerability indicator. This indicator is used to predict out of sample country specific currency crisis. The estimated common shock underlies the dynamics of few factors common to all the external debt data (see Forni et al., 2003). 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 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.

Finally, in order to account for either the financial channels we cannot control for (say herding) or for the trade linkages (see, for instance, Glick and Rose, 1998), we also consider the case of cross sectional dependence among the idiosyncratic country specific shocks in forecasting the EMP index. The idiosyncratic shock are estimated as the residuals of each country specific EMP on the estimated static factors.

The (out of sample) probability forecasts regarding the likelihood of the crisis are obtained by implementing stochastic simulation of the DF model estimated, and their accuracy is based upon the quadratic probability score (QPS), the log probability score (LPS) (Diebold and Rudebusch, 1989) and the Kuipers Score (KS) methods.

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 stylised facts and review the literature on. Section 3 the 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 easily interpreted as the probability of a crisis. However, a practical problem of using this strategy to model currency crises is the limited number of crises (e.g., there are only a few ones in the sample, compared with a large number of

zeros, resulting in poor estimation results). In order to increase the number of ones, many studies combine data from industrialised and emerging market economies (see Van Rijckeghem and Weder, 2000, among others, who apply a multivariate logit or probit model to pooled panel data). 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, Goldstein et al (2000b) and Zhuang and Dowling (2002) find some support for the use of a signaling approach-based EWS, in terms of the model out-of-sample forecasting performance. 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, and 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.

The aim of this paper is to explore the out of sample leading indicator properties of a vulnerability index regarding the index of exchange market pressure (see below). In order to construct the vulnerability indicator of currency crises we consider the suggestions given by the studies on financial contagion as explained in the next section.

3 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 tur-

bulence 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 investors 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.

While proxies for the common lender channel or maturity mismatch can be retrieved with some degree of accuracy, other financial contagion channels (say, herding) are more difficult to measure or to control for. Proxy for trade linkages are available only at annual frequency. Therefore, in the present paper, in order to account for the channel we cannot control, we retrieve a measure of residual based contagion by allowing for cross sectional dependence among the country specific shocks. The latter are obtained by estimating the residuals from the actual realisations of the exchange market pressure indices in the different countries and the corresponding fundamental based contagion component (see below).

4 Empirical methodology

In this paper, in line with the suggestion given the financial contagion literature (see above), we look at a large number of vulnerability indicators which do take into account not only the overall size of the external debt (relative to the stock of foreign reserves) but also its maturity and its geographical composition as suggested by recent third generation of currency crisis model. More specifically we pool the whole set of information provided by the different vulnerability indicators in each country, in order to obtain a measure of regional vulnerability in the East Asian region. Kaminsky and Reinhart (2000) who use a signal based method (see above) were the first to find important the role played by a regional (vulnerability) component in explaining the exchange market pressure and, consequently, to find evidence (through in sample forecasting) of fundamental based contagion. 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. However, 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. We argue that these variables, according to the financial contagion literature (see section 3), play an important role in assessing the degree of external vulnerability. Therefore, in the present paper, we retrieve disaggregate data (on biannual basis) on the external debt from the Bank of International Settlements dataset. As mentioned in the introduction, given that the external debt data are available only at low frequency, then 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, we use the principal components method suggested by Stock and Watson (2002).¹ More specifically, the probability forecasts regarding the likelihood of a crisis are obtained through Montecarlo simulation of the following equation:

$$EMP_{i,t+1} = \beta(Df_t + Ru_{t+1}) + \nu_{t+1} \quad (1)$$

The first addend of the r.h.s. of equation (1) is the one step ahead projection of the systemic component of the EMP index². In particular, the expression in brackets can be split in two components. The first addend, $A_n f_t$, denotes the anticipated component of the EMP index since f_t is function of past and current values of a regional vulnerability shock u (see below). The second addend in the brackets, Ru_{t+1} , accounts for the unanticipated impact of the common shock, occurring at time $t + 1$. Finally, ν_{t+1} measures the idiosyncratic (country specific) shock. In the following subsection we describe in detail how to estimate the common shock u and the coefficient matrices in eq. (1) that describe the systemic component of the EMP index.

4.1 Dynamic Factor

Consider the n dimensional dataset of balance sheet data x_{nt} , described as:

¹The 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.

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

$$x_{nt} = A_n f_t + \xi_{nt} \quad (2)$$

where f_t is the r dimensional vector of static factors (with $r \ll n$), and A_n is an $n \times r$ matrix of factor loadings. The static factors dynamics is described by:

$$f_t = Df_{t-1} + Ru_t \quad (3)$$

where u_t is the (structural form) common shock (interpreted as the regional vulnerability indicator) underlying the dynamics of the static factors and R measures the impact of the common shock on the static factors. The estimation of equations (2) and (3) is done in two stages. In the first stage, a consistent estimation of f_t is obtained by applying standard principal component analysis to the panel x_{nt} :

$$f_t = \sqrt{T}W \quad (4)$$

where W is the $n \times r$ matrix having, on the columns, the eigenvectors corresponding to the first r largest eigenvalues of the covariance matrix $(1/Tx_{nt}x'_{nt})$ and T is the time series dimension. In a second stage of the analysis, an *OLS* estimation method is used to retrieve the reduced form disturbances $\varepsilon_t = Ru_t$ in (3). The matrix R is obtained by using an eigenvalue-eigenvector decomposition of the covariance matrix the ε_t ³ :

$$R = KM \quad (5)$$

where:

- a) M is a diagonal matrix having the square roots of the q largest eigenvalues of covariance matrix of the residuals ε_t on the main diagonal;
- b) K is the $r \times q$ matrix whose columns are the eigenvectors corresponding to the q largest eigenvalues of covariance matrix of the residuals ε_t .

In order to compute the composite vulnerability indicator we consider: a) the case of fundamental based contagion; b) the case both fundamental based and residual based contagion. In case a) the residuals from the diffusion index

³The measurement of the impact effect of the common shock u is along the lines of Forni et al. (2003). Since we are interested in the estimation of only one common shock interpreted as a regional indicator of the crisis, the rotation matrix (see Forni et al.,) necessary for identification collapses to a scalar normalised to unity.

forecast regressions are orthogonal to each other; in case b) we allow for cross section dependence across the idiosyncratic (country specific) innovations (see below).

4.2 Stochastic Simulation

Once we obtain the estimates of the static factors f_t , of the matrix coefficients D and R , all we need is an estimation of the sensitivities β , obtained from the following OLS regression:

$$EMP_{i,t} = \beta f_t + \nu_t \quad (6)$$

to produce the one step ahead forecast through stochastic simulation of the EMP index as suggested in eq. (1). In particular, we draw the common shock u from a $N(0, 1)$ random variable⁴. Furthermore, for each common shock drawn, we draw 1000 idiosyncratic shocks from a $N(0, 1)$ distribution and this exercise is repeated 1000 times, generating 1000000 observations for the distribution of the EMP index. As for the idiosyncratic shock generation, we consider two cases. In the first case we allow the idiosyncratic shocks to be orthogonal to each other. This implies that we account only for fundamental based contagion theory to construct the vulnerability indicator used for forecasting purposes. In the second case we allow some cross sectional dependence in the idiosyncratic shocks. This implies that we allow for both fundamental based and residual based contagion to construct the vulnerability indicator used for forecasting purposes. In the latter case, the 5×1 vector of idiosyncratic shock is multiplied by the Cholesky factorization of the correlation matrix for the idiosyncratic innovations ν from eq. (1). The residuals ν are obtained from the OLS regression given in eq. (6).

4.3 Out of sample probability forecast and forecast accuracy evaluation

The out-of-sample probability forecasts are obtained using a recursive OLS (see below), so as to avoid using future information in the forecasting exercise. Finally, the probability forecast are computed by counting the ratio of the number of times the artificial series in (1) is equal or above one standard

⁴Results do not change if we allow for large realisations of the common shocks (measured as 2 or 3 standard deviations for u).

deviation from the mean of the actual realisations of the EMP index⁵.

To evaluate these probabilities, we employ the quadratic probability score (QPS), the log probability score (LPS) (Diebold and Rudebusch, 1989) and the Kuipers Score (Granger and Pesaran, 2000). The first one ranges from 0 to 2, with 0 being perfect accuracy. The second one ranges from 0 to ∞ . LPS and QPS imply different loss functions with large mistakes more heavily penalized under LPS. Let P_t the prediction probability of the event A (crisis) or B (no crisis) by the model for the next period starting at t and R_t is a binary variable, that is equal to 1 if the event occurs in the actual data and equal to 0 otherwise, then then the Briers score (QPS) and the logarithm score (LPS) are written as:

$$QPS = 1/T \sum 2(P_t - R_t)_2 \quad (7)$$

and:

$$LPS = 1/T \sum [(1 - R_t) \ln(1 - P_t) + R_t \ln(P_t)] \quad (8)$$

The Kuipers score is based on the definition of two states as two different indications given by the model: currency crisis and no currency crisis. We assume the model signal the crisis the predicted probability is larger than 0.5. So 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, $FA = false\ alarms/(false\ alarms + correct\ rejections)$:

$$KS = H - FA \quad (9)$$

⁵The choice of this threshold for the EMP index is to avoid poor estimation results, given too few ones in the sample, compared with a large number of zeros in the panel.

Kuipers scores above zero mean that the model generates proportionally more hits than false alarms.

4.4 Empirical analysis

4.5 The Data

As explained in section 2, given the important role of the total external debt (especially 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 biannual basis from the first semester of 1986 to the second semester of 2003⁶. These data measure, on a worldwide consolidated basis, the foreign claims of banks headquartered in the reporting area. The description of the disaggregate data on external debt is as follows.

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, Japan, Netherlands, Sweden, Switzerland, UK, 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 also include data on international bonds and notes issued by the five Asian emerging economies under investigation. Furthermore we consider the money supply aggregate M_2 (obtained from the International Financial Statistics, IFS, database of the IMF) in each country. 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

⁶These data are also available on quarterly basis from 1999

the presence of a weak banking system indicates a greater probability of such capital flight.

In light of the data description given above, we consider a total of 13 variables for each country (measured in millions of US dollars), and we take their ratios to the stock of official reserves foreign exchange reserves (minus gold) in millions of US dollars to obtain indicators of vulnerability. The data for the components of the EMPI index are obtained from the International Financial Statistics (IFS) of the IMF database. As suggested by Girton and Roper (1977), the measure of the EMPI 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 by base money (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.

4.6 Empirical Results

As explained above, the out of sample probability forecast are obtained through recursive *OLS* estimation. In particular, we use data available through the last semester of 1993 and then we use the estimated model to produce the first 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 twenty observations. The diffusion index forecasting equation given by (6) is augmented by lagged values for the *EMP* series (to account for serial correlation in the dependent variable, see Stock and Watson, 2002). The selection of the number of lags for the dependent variable and the r static factors entering in the diffusion index forecast equation are obtained through a recursive Bayesian information criterion, *BIC*, using data available prior to making forecast at each iteration⁷. We consider two Dynamic Factor models. The first one, based upon the assumption of orthogonal idiosyncratic shocks, produces an index of only fundamental based contagion, *FactorFBC*. The second one, allowing cross sectional dependence among the idiosyncratic shocks, produces an index including both fundamental and residual based contagion, *FactorFBC + RBC*. The (out of sample)

⁷We fix to six both the maximum lag length and the dimension of the static factor space.

forecasting performance of the two aforementioned contagion indicators is compared with various benchmarks⁸. The first one is an *AR* (where the lag order p is obtained through recursive *BIC*). The other benchmarks are given by forecasting regressions which include lags of the dependent variable and current and past values of one of the main aggregates in the dataset used to extract the factors. These series are the maturity composition of debt: *debt_1y* (up to and including one year); *debt_2y* (over one year up to two years), *debt_3y* (over two years); the total borrowing from Japan (the major international lender to the East Asian region on the eve of the crisis), *debt_Jap*; the external bond securities debt, *bond*; the ratio of M_2 to the total stock of foreign reserves; the total external banking debt, *tot_debt*. In Fig. 1-5 we plot the probability forecasts produced by the Dynamic Factor model measuring the fundamental based contagion indicator. The vertical bars denote the “ones”, measured in terms of one standard deviation from the mean of the *EMP* index in each country, and they are in total thirteen, eight of which occurring during the Asian crisis period. From the Figures, we observe that the dynamic factor model probability forecast predicts correctly four out of the eight crisis events during the 1997-1998 period, whereas none of the benchmark models (see, for instance, Fig 6-10, where we plot the probability forecasts associated with the *AR* model) is capable to predict any of the crisis events hitting the *EMP* series⁹. The good performance of the fundamental based contagion indicator obtained through the Dynamic Factor model is reflected in the associated Kuipers score, *KPS*, which shows that the proportion of hits is higher than the proportion of false alarms in all countries but Philipines (see Table 1). On the other hand, even though in terms of the *QPS* and *LPS* scores, the dynamic factor model does not perform better than any model (see Table 1), the Kuipers score associated with the benchmark models is either zero or negative, given that the corresponding probability forecasts consistently predict no crisis. Furthermore, once we consider a dynamic factor model describing both fundamental based and residual contagion (see fourth row of Table 1), we do not obtain any improvement in the forecast produced by only the fundamental based contagion model. This leads us to conclude in favour of a fundamental based

⁸The probability forecast corresponding to each benchmark are obtained through 1000 draws from an $N(0, 1)$ distribution of each of the idioncratic shocks.

⁹The probability forecasts associated with the other benchmark models considered are available upon request.

contagion model for the purpose of EMP forecasting ¹⁰. Therefore, in line with the study of Kaminsky and Reinhart (1999), we argue that the evidence for contagion can be mainly explained through financial linkages, explained by the large short-term external borrowing from a common lender country. Throughout the 1990s, among the major international lenders, Japan was heavily exposed country to emerging Asia. Japanese banks, already in fragile conditions after the burst of the 1980s asset bubble and weakened by a stagnant economy in the 1990s, had heavily lent to other Asian economies. Given the very low interest rates in Japan, large scale lending to the fast growing East Asian countries was stimulated by the higher returns available outside Japan. As of June 1997, Japanese banks held 37% of all claims on counterparts in the five seriously affected countries¹¹. Following the onset of the Asian crisis, foreign claims on Asian counterparts shifted significantly. An analysis of both the maturity and sectorial composition of the claims of the Bank for International Settlements (BIS) reporting countries, shows, by the end of 1997, a non renewal of short term credit lines on emerging Asian countries, especially for the corresponding banking sectors. As explained above, pulling out of emerging Asia can be explained by the margin calls on the group of leveraged informed financial investors arising especially in presence of maturity and currency mismatches (the short term claims to the five seriously affected countries in East Asia amounted to roughly 64% of total claims, following a relatively stable trend since 1993)

¹⁰We do not report the plot of the probability forecasts for the dynamic factor model describiing both fundamental based and residual contagion, given that they are very similar to those produced in Fig. 1-5. Results are available upon requests.

¹¹European bank lending to emerging Asia was also significant (by June 1997 European banks held 37% of all claims on counterparties in the five seriously affected countries), whereas US bank exposure to Asia was modest on the eve of the crisis (accounting only to 9% of the total claims).

Table 1: Forecasting Results									
	Indonesia			Malaysia			Phillipines		
	<i>QPS</i>	<i>LPS</i>	<i>KPS</i>	<i>QPS</i>	<i>LPS</i>	<i>KPS</i>	<i>QPS</i>	<i>LPS</i>	<i>KPS</i>
<i>FactorFBC</i>	0.19	0.52	0.44	0.37	0.61	0.18	0.27	0.44	-0.05
<i>FactorFBC + RBC</i>	0.21	0.57	0.44	0.38	0.62	0.18	0.28	0.44	-0.05
<i>AR</i>	0.19	0.69	0.00	0.39	1.38	0.00	0.19	0.69	0.00
<i>debt_1y</i>	0.17	0.31	0.00	0.33	0.54	0.00	0.19	0.35	0.00
<i>debt_2y</i>	0.18	0.34	0.00	0.34	0.55	0.00	0.19	0.37	0.00
<i>debt_3y</i>	0.18	0.35	0.00	0.35	0.58	0.00	0.18	0.35	0.00
<i>debt_Jap</i>	0.18	0.33	0.00	0.34	0.55	0.00	0.18	0.35	0.00
<i>bond</i>	0.19	0.36	0.00	0.33	0.53	0.00	0.19	0.35	0.00
<i>m2_res</i>	0.18	0.33	0.00	0.34	0.57	0.00	0.19	0.35	0.00
<i>tot_debt</i>	0.18	0.33	0.00	0.34	0.55	0.00	0.18	0.35	0.00

Table 1 (cont.): Forecasting Results							
	Korea			Thailand			
	<i>QPS</i>	<i>LPS</i>	<i>KPS</i>	<i>QPS</i>	<i>LPS</i>	<i>KPS</i>	
<i>FactorFBC</i>	0.30	0.57	0.33	0.29	0.85	0.44	
<i>FactorFBC + RBC</i>	0.31	0.58	0.33	0.29	0.58	0.44	
<i>AR</i>	0.19	0.61	0.00	0.31	0.95	-0.05	
<i>debt_1y</i>	0.19	0.35	0.00	0.20	0.44	0.00	
<i>debt_2y</i>	0.19	0.35	0.00	0.20	0.41	0.00	
<i>debt_3y</i>	0.19	0.34	0.00	0.21	0.46	0.00	
<i>debt_Jap</i>	0.18	0.33	0.00	0.20	0.43	0.00	
<i>bond</i>	0.18	0.33	0.00	0.20	0.42	0.00	
<i>m2_res</i>	0.18	0.33	0.00	0.19	0.41	0.00	
<i>tot_debt</i>	0.19	0.34	0.00	0.20	0.42	0.00	

5 Conclusions

Most of the empirical studies on the predictability of currency crises have been based upon in sample forecasting analysis. In this paper we are interested in the out of sample predictability of balance of payment crises, through a regional indicator of vulnerability. For this purpose we fit a Dynamic Factor model to a large number of balance sheet data across five emerging market countries in the East Asian region and we use stochastic simulation to produce probability forecasts out of sample. Given that the the factors extraction is obtained by minimising the noise (which captures the measure-

ment error contaminating the variables entering in a dataset) to signal ratio, the composite vulnerability indicator obtained through DF improves over a number of benchmark models in terms of forecasting performance, in terms of the Kuipers score. Specifically, the empirical findings suggest evidence of fundamental based contagion in predicting the currency crises involving the five largest economies in emerging Asia during the 1997-98 period.

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Figure 1: Dynamic Factor out of sample probability forecast for Indonesia

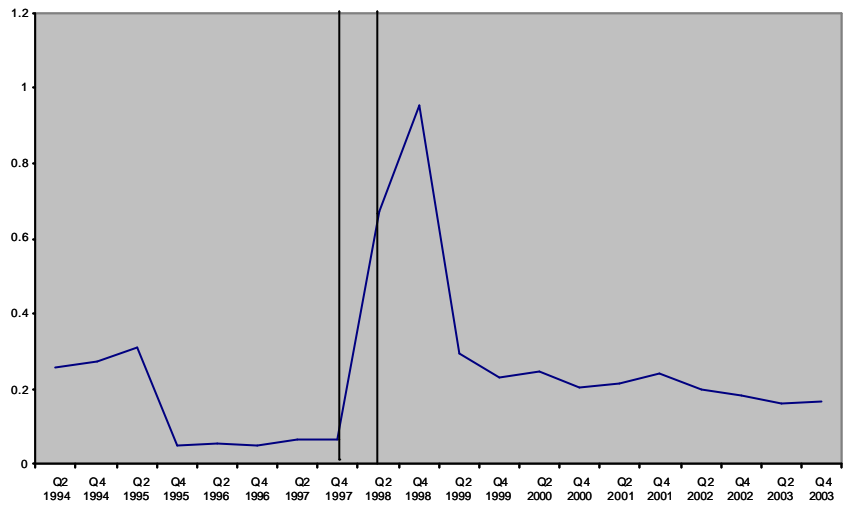


Figure 2: Dynamic Factor out of sample probability forecast for Malaysia

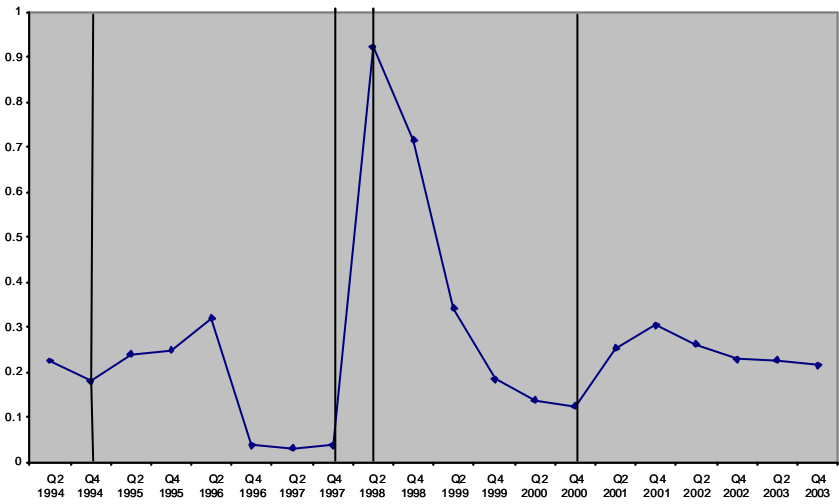


Figure 3: Dynamic Factor out of sample probability forecast for Philippines

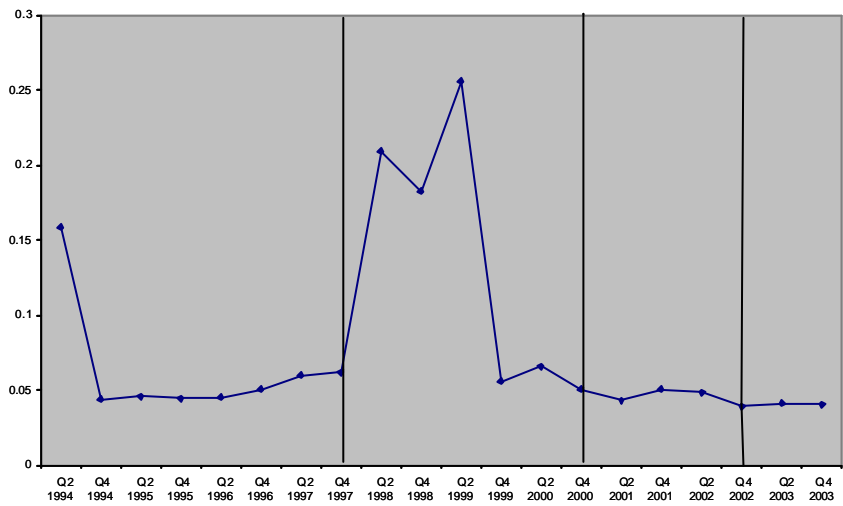


Figure 4: Dynamic Factor out of sample probability forecast for Korea

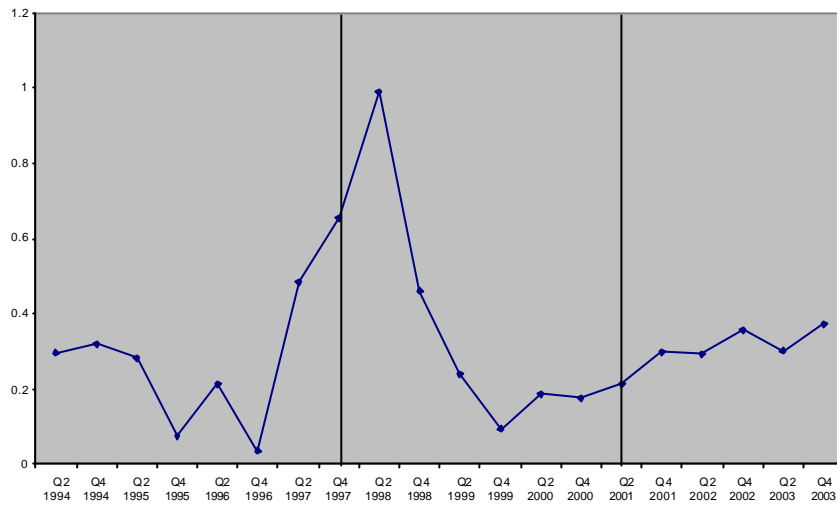


Figure 5: Dynamic Factor out of sample probability forecast for Thailand

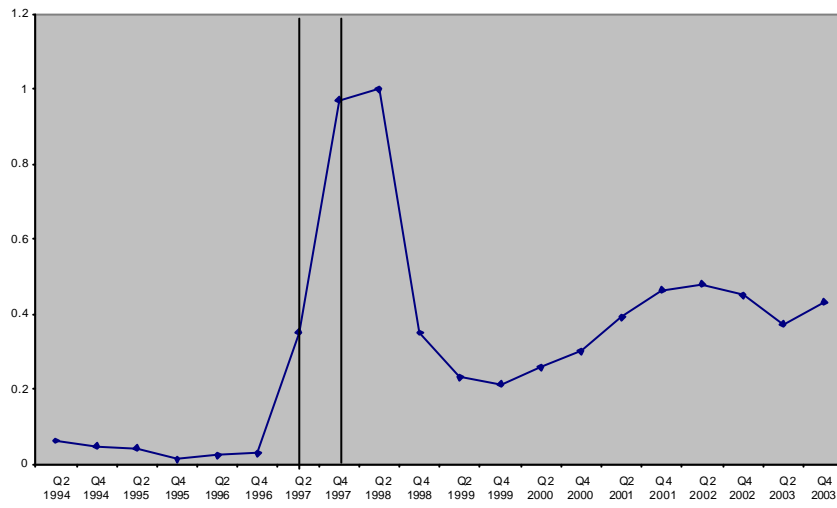


Figure 6: AR out of sample probability forecast for Indonesia

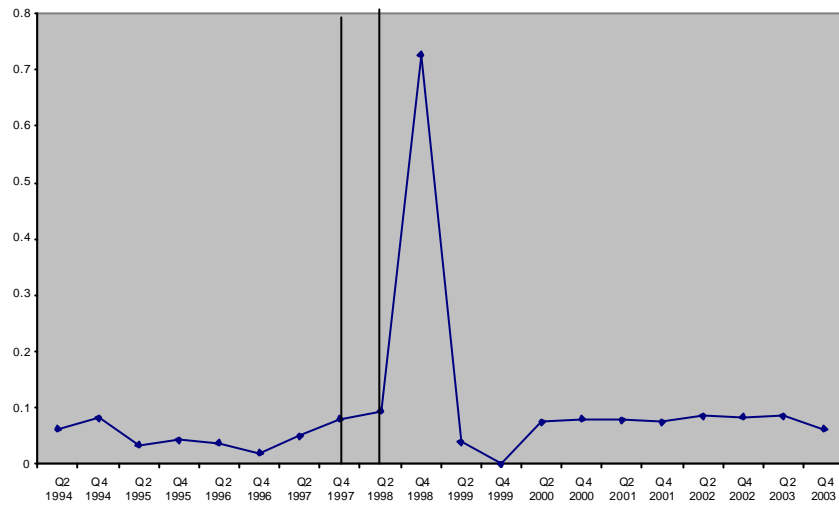


Figure 7: AR out of sample probability forecast for Malaysia

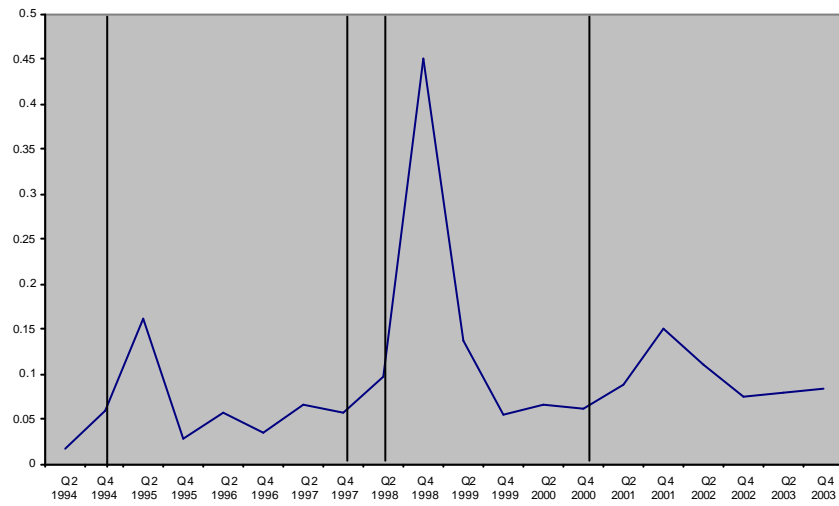


Figure 8: AR out of sample probability forecast for Philippines



Figure 9: AR out of sample probability forecast for Korea

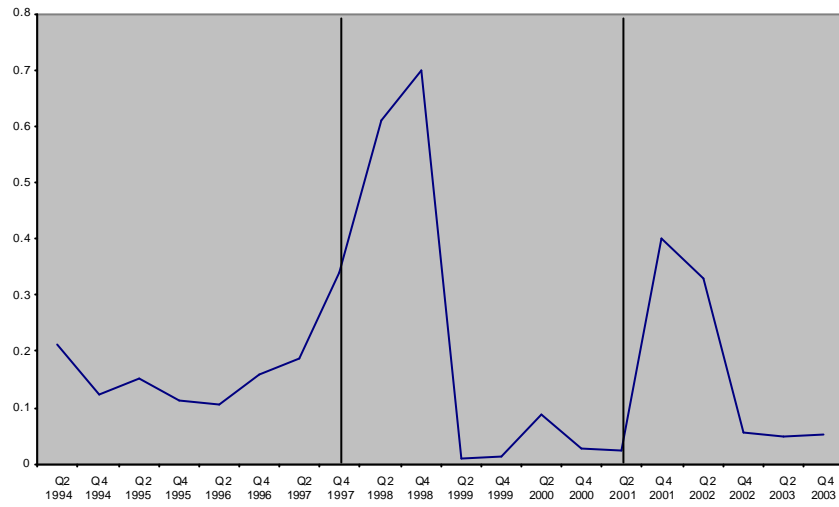
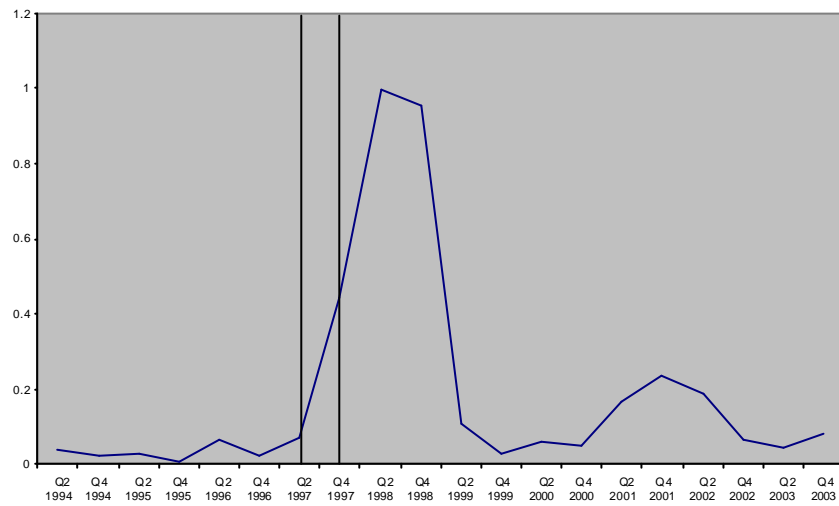


Figure 10: AR out of sample probability forecast for Thailand



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