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Abstract

We tackle explicitly the issue of model uncertainty in the framework of binary variable models of currency crises. Using Bayesian model averaging techniques, we assess the robustness of the explanatory variables proposed in the recent literature for both static and dynamic models. Our results indicate that the variables belonging to the set of macroeconomic fundamentals proposed by the literature are very fragile determinants of the occurrence of currency crises. The results improve if the crisis index identifies a crisis period (defined as the period up to a year before a crisis) instead of a crisis occurrence. In this setting, the extent of real exchange rate misalignment and financial market indicators appear as robust determinants of crisis periods.

Keywords: Currency crisis, Bayesian model averaging.

JEL classification: F31, F34, E43.

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1 Introduction

Over the course of the last couple of decades several parts of the world have experienced rather harsh financial market crises, sometimes repeatedly, and mostly accompanied by painful real shocks. The very last wave of such turmoils, initially triggered on the US (subprime) mortgage market, has exemplified that financial market turbulences are not confined only to the developing and emerging economies. Moreover, the recent tensions have clearly unveiled challenges financial stability authorities and policy makers have to face in the age of ever deeper and more global markets. Most importantly, diminishing barriers to capital flows and instant information distribution increase the potential sudden evasiveness of capital. As evidenced by the shocking promptness with which the US mortgage malaise extended from one corner of the financial market to another, crises can spread swiftly between different types of markets in geographical and technical terms.

One of the most frequent targets of speculators is the currency market and substantial devaluations of the currency under attack generally imply severe consequences for the respective economy. Against this backdrop it is not surprising that both in the academic literature and in the private sector a variety of empirical attempts has been undertaken to predict currency crises. Following the pioneering indicator approach by Kaminsky, Lizondo and Reinhart (1998) a whole plethora of early warning systems for currency crises has been developed. Some of the rather recent approaches employ innovative methodologies such as Markov switching models (see e.g. Abiad, 2003 or Chen, 2005) or financial market tools (see e.g. Malz, 2000 or Crespo Cuaresma and Slacik, 2007) to predict currency attacks.

The vast majority of the empirical literature assesses the effect of various potential determinants on the probability of a currency crisis using limited dependent variable - logit or probit - models. The discrete crisis variable is regressed on a set of fundamental indicators, such as, inter alia, current account and government balances, exchange rate overvaluation or liquidity ratios . The choice of regressors is typically inspired by the three generations of theoretical models on balance-of-payment crises. In one of the most recent empirical contributions on this topic Bussière (2007) overhauls the usually static specification, in which, moreover, all regressors tend to enter at the same lag. He thus extends the usual set of explanatory variables by including several lags of the regressors as well as of the dependent binary crisis variable. He finds that there are several variables significantly affecting the probability of a crisis in a dynamic logit model. However, the impact of the indicators ranges between short-run (4-6 months) e.g. for the liquidity measures to very long-run (2 years) in case of over-appreciation of the exchange rate. In addition, his results indicate that past crisis episodes increase the probability of a new attack, particularly in the short run.

Notwithstanding substantial variations in the literature on early warning systems with respect to methodology, data as well as results, there is one general caveat which applies to all existing binary choice models. Given that there is no unique theoretical framework linking the potential set of determinants with the realizations of currency crises, the issue of model uncertainty surrounding both the choice of variables and the estimates obtained deserves to be treated seriously. Model uncertainty can be explicitly taken into account using Bayesian statistical techniques, in particular with the use of the Bayesian model averaging (BMA) methodology which proposes averaging of the paramaeter values over all (relevant) alternative models using posterior model probablities as respective weights to evaluate the relative importance of different variables (see Raftery, 1995 for a general discussion and Sala-i-Martin *et alia*, 2004, Fernandez *et alia*, 2001, or Crespo Cuaresma and Doppelhofer, 2007 for applications to economic growth regressions).

The different theoretical settings used to explain different crises episodes give rise to alternative sets of potential explanatory variables (with intersections which are not necessarily empty) for the probability of a crisis ocurring. The so-called *first generation* models (Krugman, 1979, Flood and Garber, 1984) concentrate on bad economic policy leading to unsustainable developments of some fundamental macroeconomic variables. The abandonment of the fixed exchange rate regime is then precipitated by the eventual exhaustion of the central bank's foreign reserves. The *second generation* of currency crises models (see for instance Obstfeld, 1994), explains crises as the consequence of self-fulfilling expectations in theoretical settings with multiple equilibria. In contrast, the *third generation* of models (Krugman, 1998) explains the outbreak of a currency run as a symptom of accumulated problems in the banking and financial sector. In the theoretical setting, government guarantees aimed at attracting foreign investment lead to a bubble on the asset market that eventually bursts and creates the crisis. Obviously, given the different theoretical nature of the ultimate cause of the currency crises in the different generations of models, the potential empirical determinants to be included in econometric studies vary strongly depending on the theory used to select covariates.

The objective of the present paper is to revisit binary-variable models for currency crises based on macroeconomic fundamental data by explicitly taking into account model uncertainty. In particular, we want to work out to what extent model uncertainty puts the robustness of the explanatory variables of the logit models championed in the literature (e.g. Bussière and Fratzscher 2006 or Bussière 2007) under strain. On the one hand, our results indicate that the usual macroeconomic variables used in empirical studies of currency crisis are very fragile determinants of the occurrence of such episodes. On the other hand, if we redefine the crisis indicator as to give a signal for observations up to one year prior to the crisis, several variables appear as robust determinants of these crisis periods. Financial market indicators and the deviations of the real exchange rate from a linear trend present very high posterior model inclusion probabilities and thus can be considered robust determinants of crisis periods.

The remainder of the paper is structured as follows: Section 2 sketches the Bayesian model averaging procedure. In section 3 the data are described and variables defined. Section 4 presents the results on the extent to which model uncertainty matters, while section 5 concludes.

2 Dealing with model uncertainty: Bayesian model averaging

The binary variable we are interested in modelling takes value one if a currency crisis occurs in period t ($y_i = 1$) and zero if no currency crisis is observed ($y_i = 0$). A stereotypical regression aimed at assessing the effect of a set of variables $\{\mathbf{x}_j\}_{j=1}^{K}$ on the probability of a currency crisis occurring is given by

$$\mathrm{P}(y_i = 1 | \{\mathbf{x}_j\}_{j=1}^{K}) = F(\mathbf{X}_K \beta), \tag{1}$$

where $F(z)$ will typically be a logistic function ($F(z) = (1 + e^z)^{-1}$) or the distribution function of a normal random variable ($F(z) = \Phi(z)$), $\mathbf{X}_K = (x_1 \ \dots \ x_K)$, which is a subset of $\mathbf{X}_{\bar{K}} = (x_1 \ \dots \ x_{\bar{K}})$, containing all possible regressors ($\bar{K} > K$ of them), and $\beta = (\beta_1 \ \dots \ \beta_K)'$. In principle, many candidate variables can be proposed as potential covariates in (1).

So far, the literature tends to concentrate on an arguably tiny subset of this model space. Model averaging techniques propose averaging over all these alternative models using Bayes factors so as to evaluate the relative importance of different variables as determinants of the occurrence of a currency crisis. In the situation where there are M competing models, $\{M_1, \ldots, M_M\}$, which are defined by the choice of independent variables, so that $M = 2^{\bar{K}}$, Bayesian inference about the parameter of interest, β_i is based on its posterior distribution (that is, the distribution given the data, $\mathbf{Y} = \{y \;\; \mathbf{X}_K\}$),

$$\mathrm{P}(\beta_i|\mathbf{Y}) = \sum_{m=1}^{M} \mathrm{P}(\beta_i|\mathbf{Y}, M_m)\mathrm{P}(M_m|\mathbf{Y}), \tag{2}$$

where the posterior probabilities $\mathrm{P}(M_k|\mathbf{Y})$ are given by

$$\mathrm{P}(M_k|\mathbf{Y}) = \frac{\mathrm{P}(\mathbf{Y}|M_k)\mathrm{P}(M_k)}{\sum_{m=1}^{M}\mathrm{P}(\mathbf{Y}|M_m)\mathrm{P}(M_m)}. \tag{3}$$

The posterior model probabilities can thus be obtained as the normalized product of the integrated likelihood for each model ($\mathrm{P}(\mathbf{Y}|M_k)$) and the prior probability of the model ($\mathrm{P}(M_k)$). Notice that for the simple case $m = 2$ the posterior odds for a model against the other can be readily written as the product of the Bayes factor and the prior odds. Further assuming equal priors across models, the posterior odds are equal to the Bayes factor ($\mathrm{P}(\mathbf{Y}|M_2)/\mathrm{P}(\mathbf{Y}|M_1)$). The Bayes factor, in turn, can be accurately approximated (see Leamer, 1978, and Schwarz, 1978) as

$$\frac{\mathrm{P}(\mathbf{Y}|M_2)}{\mathrm{P}(\mathbf{Y}|M_1)} = N^{(k_1-k_2)/2}\left(\frac{Lik_2}{Lik_1}\right), \tag{4}$$

where N is the number of observations, k_j and Lik_j are respectively the number of parameters and the likelihood of model j. This simple approximation allows us to compute (3) and the corresponding statistics based on (3).

This implies that for a given prior on the model space, the posterior distribution of β can be obtained as a weighted average of the model-specific estimates weighted by the posterior probability of the respective models. If the cardinality of the model space is computationally tractable, (3) can be obtained directly and (2) can be computed. In particular, the expected value of β and its variance, $\mathrm{E}(\beta|\mathbf{Y})$ and $\mathrm{var}(\beta|\mathbf{Y})$ respectively, can be computed as follows

$$\mathrm{E}(\beta_i|\mathbf{Y}) = \sum_{m=1}^{M} \mathrm{E}(\beta_i|\mathbf{Y}, M_m)\mathrm{P}(M_m|\mathbf{Y}), \tag{5}$$

$$\mathrm{var}(\beta_i|\mathbf{Y}) = \sum_{m=1}^{M} [\mathrm{var}(\beta_i|\mathbf{Y}, M_m) + \mathrm{E}(\beta_i|\mathbf{Y}, M_m)^2]\mathrm{P}(M_m|\mathbf{Y}) - \mathrm{E}(\beta_i|\mathbf{Y})^2. \tag{6}$$

The posterior mean and variance can be used to make inference on the quantitative effect of changes in the covariates on the probability of a currency crisis explicitly taking into account model uncertainty. Several methods have been proposed for approximating the expression in (3) when the cardinality of the model space makes the problem intractable. The *leaps and bounds* algorithm, the use of Markov Chain Monte Carlo Model Composite (MC^3) methods or the use of Occam's window are possible methods of setting bounds to the number of models to be evaluated when computing (3) (see Raftery, 1995, for an excellent description of these methods).

In our empirical application we will use a simple MC^3 algorithm to evaluate the posterior distribution based on the work of Madigan and York (1995), also used recently by Fernández *et alia* (2001) in the framework of cross-country growth regressions.[1] This Markov Chain Monte Carlo method implements the Random Walk Chain Metropolis-Hastings algorithm in the model space as follows. In a given replication s of the algorithm, a candidate model M^{s+1} is proposed, which is randomly drawn from the group of models composed by the model which is active in that replication (M^s), the same model with an extra variable added to the specification and the same model with a variable removed. The proposed model is accepted with a probability given by

$$\alpha(M^s, M^{s+1}) = \min\left[\frac{\mathrm{P}(\mathbf{Y}|M^{s+1})\mathrm{P}(M^{s+1})}{\mathrm{P}(\mathbf{Y}|M^s)\mathrm{P}(M^s)}, 1\right],$$

which is just the Bayes factor comparing M^s and M^{s+1} if equal prior probability is assumed across models, so that $\mathrm{P}(M^s)$ and $\mathrm{P}(M^{s+1})$ cancel out in the expression above. This algorithm is repeated a large number of times, and the sums defined above are computed for the group of models replicated, which will tend to cover model subspaces with the highest posterior probability.

In the same fashion, posterior inclusion probabilities for the different variables can be obtained by summing the posterior probability of models containing each variable. This measure captures, thus, the relative importance of the different covariates as determinants of the occurrence of a currency crisis and can be interpreted as the probability that a given variable belongs to the true specification.

[1] Koop (2003) also describes the method thoroughly.

3 Data and variable descriptions

3.1 Data description

The early warning system for currency crises dealt with in this paper is derived from a binary-variable model based on macroeconomic fundamental data, in the spirit of the classical contributions by, for instance, Frankel and Rose (1996). Since currency crises are events which occur seldom, in this type of models it is necessary to pool country/time data in order to increase the number of observations and obtain sufficient degrees of freedom. Naturally, this procedure implicitly imposes the assumption of parameter homogeneity across countries and in the time dimension. The resulting first requirement on our sample thus was that the crises episodes considered be sufficiently homogeneous, that is, characterized by a similar development of fundamentals. In addition, however, it was also desirable in this context to employ the same data source as a recent benchmark study using a 'standard' binary-variable approach (that is, without explicitly dealing with model uncertainty) in order to be able to figure out the value added by our model averaging procedure.

For these reasons, we decided to use as a yardstick for comparison the dataset of one of the most recent papers on this issue by Bussière (2007), who exercised great care in constructing a sample sufficiently homogenous so that common fundamental development driving the crises may be expected. Against this backdrop the overall sample consists of a pool of observations on 27 countries recorded from January 1994 to March 2003 and contains approximately 1400 observations[2]. Observations prior to 1994 are taken out of the sample to avoid biases emanating from hyperinflationary experiences in Latin American countries and the early years of transition towards a market economy in Eastern European economies.[3]

The dependent binary variable is defined to equal one if a crisis occurs and zero otherwise. Although in the common understanding a currency crisis might be associated

[2]The countries included in the sample are Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, Venezuela, China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Singapore, Thailand, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia, Slovak Republic, Slovenia, Turkey

[3]Bussière and Fratscher (2006) tested for slope homogeneity in a very similar dataset by comparing out-of-sample forecasts based on the parameter homogeneity assumption. From the good forecasting performance they conclude that the same parameter vector is suitable for different countries and episodes. In contrast, the sample used by Peltonen (2006) which contains also data on crises from the 1980s suggests significant difference between Latin America and Asia.

predominantly with a dramatic devaluation of the exchange rate, the literature on early-warning mechanisms usually tends to employ a broader definition of currency distress by using the concept of exchange market pressure. Although the latter is not uniformly defined in the literature it is usually a weighted average of some combination of the change of the real or nominal exchange rate, the country's foreign reserves and the real interest rate. The dependent variable is thus computed in two steps. First, the exchange market pressure index ($EMPI_{i,t}$) for country i at time t is defined as

$$EMPI_{i,t} = \omega_{RER}\left(\frac{\Delta RER_{i,t}}{RER_{i,t-1}}\right) + \omega_r\left(\Delta r_{i,t}\right) - \omega_{res}\left(\frac{\Delta res_{i,t}}{res_{i,t-1}}\right),$$

where RER stands for the real effective exchange rate, r is the short-term real interest rate and res the level of international reserves. In the next bout this continuous variable is transformed into a binary index which equals one whenever $EMPI_{i,t}$ exceeds the threshold of the country-specific mean ($\overline{EMPI}_i$) plus twice its standard deviation (σ_{EMPI_i}),

$$CI_{i,t} = \begin{cases} 1 & \text{if } EMPI_{i,t} > \overline{EMPI}_i + 2\sigma_{EMPI_i}, \\ 0 & \text{otherwise.} \end{cases}$$

The choice of the explanatory right-hand side variables in (1) is motivated by the theoretical literature on currency crises on the one hand and by the results of the existing empirical early warning models on the other. Table 1 lists the complete final set of variables, different combinations and transformations of which are used in the estimations below.

- Include Table 1 about here -

The exchange rate variable is supposed to capture any excessive real overvaluation of the currency, which would be expected to increase the risk of devaluation. It is defined as the deviation of the real exchange rate from a linear trend. Since data on non-performing loans are barely available for under-reporting reasons, the lending boom indicator is meant to serve as a proxy and is defined as the deviation of the credit to the private sector ($CPS_{i,t}$) from a one year average with a two year lag. The short-term-debt-to-reserves ratio (and analogously the total debt indicator) reflect the so called Greenspan-Guidotti rule which states that reserves should cover entirely the amount of external debt that can be sold short-term by investors in case of an attack. A rise of this indicator can thus stem from either a rise in debt or a fall of reserves and should render a crisis more likely. The total debt indicator is defined analogously for two different definitions: the locational (lc) and the consolidated concept (cc).[4] The set of explanatory variables further contains the current account and government surpluses, both normalized with the respective country's GDP. The sign of these two indicators is expected to be negative as the higher the surplus (the lower the deficit) the lower should be the probability of an attack. Since Bussierè and Fratscher (2006) show that contagion accross countries is only significant via the financial and not via the trade channel, only the former was taken into account in Bussière (2007). Financial interlinkages of a country i with all other countries in the sample are modeled as the average of the other countries' $EMPI_{j,t}$ ($j = 1$ to $N-1$, $j \neq i$) weighted by the correlation of equity market returns in country i and country j . Intuitively, the parameter attached to this variable should show up positive in the estimation results. The three subsequent Datastream indices, a broad market index and two sub-indices on banks and financial institutions, account for the predictive power of financial markets. They are defined as a 12-months percentage change of each stock index and are expected to enter with a negative coefficient. Finally, the year-on-year GDP growth is included as higher economic growth should reduce the government's temptation to devalue on its currency, e.g. in order to gain competitiveness. [5]

4 Empirical results: How much does model uncertainty matter?

4.1 Results for the "crisis occurrence" indicator

Following Bussière (2007), we present results based on three types of specification. Firstly, we deal with a purely static model, where lags of the dependent variable do not appear as extra regressors in the model, although all explanatory variables are evaluated with one month lag with respect to the crisis variable. We then address dynamic models, which on top of the exogenous set of variables employed in the

[4]The locational banking statistics gather data on international financial claims and liabilities of bank offices resident in the reporting countries on a gross (unconsolidated) basis, including those vis-à-vis own affiliates. In contrast, the consolidated concept covers claims reported by domestic bank head offices, including the exposures of their foreign affiliates, and are collected on a worldwide consolidated basis with inter-office positions being netted out. For details see Bank for International Settlements (2003).

[5]Further details on the construction of the variables and the intuition behind their choice can be found in Bussière (2007)

static model also include up to six lags of the crisis index as explanatory variables. Finally, the most general specification includes up to 24 lags of six selected variables $(REERDEV, LB, STDR, \frac{CA}{GDP}, CONT, GROWTH)$.[6]

In Table 2 we report the results of the BMA exercise for the static case, where all specifications in the model space have been evaluated in order to compute posterior inclusion probabilities and posterior expected values of the parameters.[7] We also deal explicitly with the issue of potential multicollinearity among the regressors. The first two columns of the table show the posterior expected values of the parameters corresponding to each variable (first column) and the posterior inclusion probabilities (second column) for the BMA exercise using all variables in Table 1. Under the header *Static uncorrelated* the results are presented for the BMA exercise after taking out variables whose correlation with some other explanatory variable was equal to or greater than 0.5 (both total debt indicators and one of the Datastream indices are the variables which do not enter this exercise).

- Include Table 2 about here -

These posterior expected values of the parameters can be compared with the results reported in Bussière (2007), which are shown in the fifth column for the simple static model and in column six for the static model with fixed effects. Since Bussière alternates the set of included variables to avoid multicollinearity we report here the range in which his (significant) estimates fall ($n.s.$ stands for non-significant, if no estimate on at least the 10%-level was available). Two facts call attention when considering the results in Table 2. First of all, the posterior expected parameter values have mostly the expected sign. The probability of a crisis thus tends to increase with the lending boom, debts relative to reserves, the contagion indicator and the deviation of the exchange rate from its trend. In contrast, robust growth and rising market indices and current account surpluses reduce the risk of a currency attack. The only somewhat counter-intuitive result, consistently confirmed in all estimations, is the

[6]Bussière (2007) also estimates models with fixed effects and reports that the hypothesis that all country fixed effects are equal to zero can be rejected, but admits that the p-value of the test is close to 10%. Conditional logit models are also estimated by Bussière (2007) for both the static and the dynamic model, with results which are very close to those from the model where no fixed effects were used.

[7]In order to keep the table readable, we do not report the posterior variances of the parameters, which are available from the authors upon request.

positive sign of the government balance variable.[8]

However, the lack of robustness of the relationships under study shows up when considering the posterior inclusion probabilities reported in Table 2. Since we assign equal prior probability to all models when computing the posterior model averaged objects, our prior on the inclusion probability of each variable is 0.5.[9] After observing the data, the probabilities of including each variable decreases strongly with respect to the prior, with none of the posterior probabilities being higher than 10%. To put it differently, the model with the greatest posterior probability (in fact one that is very close to 1) implies a constant crisis probability which is not country or time-specific (that is, the model including only a constant).

Table 3 is constructed in the same manner as Table 2 for the case of the dynamic model, including lags of the dependent variable. With the exception of the government balance variable, all variables show up again with the expected signs which coincide with those obtained by the benchmark study, when they are significant. However, except for the market indices, this time our coefficients appear to be substantially smaller in magnitude than Bussière's (2007). The posterior inclusion probabilities are once more well below the 0.5 threshold. In other words, the inclusion of six de-facto new variables does not lead to any improvement of the explanatory power of macroeconomic fundamentals. Bussière finds that the dependent variable is significant only at lag 5 and 6 in both models, with and without fixed effects. The interpretation of this result is that crises sometimes hit in two waves such that the first attack is often followed by a second bout within a short time distance. In this context, it is also interesting to note that all the coefficients of the lagged crisis index in our and Bussière's regressions enter with a positive sign. Hence, past crises tend to increase the likelihood of repeated attacks, a result which is not quite obvious ex-ante. On the one hand, a country that has experienced a crisis may be deemed more vulnerable by investors which would speak for a positive sign. On the other hand, however, two arguments can be proposed why crises in the past might reduce the probability of an attack in the future. In the short run, after a currency run there is not much speculative capital left to be withdrawn. Moreover, in the longer

[8]However, it should be borne in mind that the sample for all estimations starts in 1994, and it is a well known fact that first generation models generally fail to explain crises in the 1990s. Second and third generation models might actually get some support by this somewhat surprising result (see for example Krugman, 1996 and Bussière, 2007).

[9]There are $2^{\bar{K}-1}$ models including a given variable and $2^{\bar{K}}$ total models, so the prior inclusion probability of a given variable is $2^{\bar{K}-1}/2^{\bar{K}}$=0.5.

run, one can argue that the country previously hit has improved its vigilance and supervision mechanisms which should render a repeated crisis less likely.

- Include Table 3 about here -

In order to account for a general dynamic structure in the model, Bussière (2007) regresses in a standard logit model (without fixed effects) the dependent variable on six chosen explanatory variables ($REERDEV, LB, STDR, \frac{CA}{GDP}, CONT, GROWTH$) which are all lagged by 1 to 24 months. This series of regressions thus provides him with 24 different models and 144 different coefficients from which the author draws the conclusion that *"some variables have a very short-term impact, such as the short-term debt to reserve ratio, some have both a very short-term and a longer term impact (such as the contagion variable), some have a short- to medium-term impact (such as the lending boom), some always seem to have an impact (such as the exchange rate), while for growth and the current account, no impact can be detected"* (Bussière, 2007, page 26). We conducted a different exercise at this point and constructed the BMA procedure using as explanatory variables six lags of the crisis variable and 24 lags of all 12 variables listed in Table 1, all at the same time. Hence, this setting contains 294 potential explanatory variables which imply 2^{294} (more than 3×10^{88}) different models over which we have to average. Given the fact that, with the current technology, this does not appear possible in a lifetime[10], we used the MC^3 approach described above to evaluate the posterior objects.

In table 4 we confine ourselves to reporting only the results for the lags of each variable with the highest posterior inclusion probability.[11] Focusing on the coefficients in the second column one can note that some of the signs now have changed into an unexpected direction. The government surplus, which used to carry a counterintuitive positive coefficient now has got the "right", negative sign, while more robust growth, higher current account surpluses and lower lending suddenly and counter-intuitively increase the probabiliy of a crisis - at least for the lags with the highest inclusion probability. As if this was not puzzling enough, the sign of the coefficients is not uniform for all lags but rather alternates from positive to negative for all variables. Interestingly enough, the fluctuation pattern looks to a great

[10]If it took only 0.001 second to estimate one model the whole calculation would last 1.009 $\times 10^{78}$ years. Although the reasoning put forward above could also imply that interactions between long and short-term variables play an important role in unwinding currency crises, due to the extra computational burden imposed by the use of cross-products, we do not embark in this type of exercise in the present study.

[11]The complete set of results is available from the authors.

extent similar to the one derived by Bussière (2007). In his estimations growth, for instance, only has the expected negative sign for lags 1 to 8 and 16 to 19. Similarly, current account surpluses lagged by more than 11 months increase the probability of a crises. The latter is also more likely the lower was the lending boom 18 months or more ago. It has to be added, however, that growth, current account and the lending boom from lag 13 on are not significant (see Figures 1 to 4, which present the parameters estimated by BMA against Bussière's results).

- Include Figures 1, 2, 3 and 4 about here -
- Include Table 4 about here -

Among the remaining variables which carry the same sign as in the previous calculations (for the lag with the highest posterior inclusion probability at least) it strikes that the effect of the lagged crisis binary variable is again the most robust at lag 5. In addition, the effect of the exchange rate deviation from trend is now almost twenty times bigger than in Tables 2 and 3. This is because the coefficent of the exchange rate variable shows a strong bell-shaped form, rising strongly between lags 4 and 10 and decreasing sharply after that. This contradicts somewhat Bussière's results according to which the exchange rate effect seems much more homogenous and significant for all lags. Lastly, it may also be pointed out that all market signals seem to be most symptomatic of tension on the exchange rate market 2 years in advance, which is not quite easy to interpret either.

As can be seen in the third column of Table 4 which displays the lag with the maximum posterior inclusion probability for each variable all values but one are far beyond good and evil. Only the deviation of the exchange rate from trend at lag 10 shows up with a posterior inclusion probability above the prior of 0.5. Although the importance of the variable is clear, by no stretch of imagination we can think of any plausible explanation for the fact that only the tenth lag appears robust, and even less so if considering the fact that the second highest inclusion probability for this variable (at lag 9) is more than ten times smaller. We thus argue that it is just a matter of coincidence and that also in this exercise fundamentals have proven to have no systematic and robust explanatory power for currency crises.

4.2 Results for the "crisis period" indicator

The results presented above are based on a crisis index which indicates a crisis in a particular month if the continuous exchange market pressure index exceeds a certain threshold in that month. In other words, a model based on this definition of a crisis attempts to predict the exact timing of a crisis in a given country. As we have shown, if we employ this crisis definition and address model uncertainty in a Bayesian manner we, unlike Bussière (2007), find virtually no robustness of the potential explanatory variables. The model-based results by Bussière (2007), however, do not perform too well in terms of prediction. It is argued in Bussière (2007) that, by trying to predict the exact month of a crisis, the model attempts to achieve something that may simply be infeasible. In order to address this caveat the time window of the crisis definition is extended to a whole year. Hence, a crisis signal is now issued not only if a strong depreciation occurs within a month but if the $EMPI$ exceeds the threshold in any of the successive 12 months. The corresponding (transformed) crisis indicator (TCI) is thus

$$TCI_{i,t} = \begin{cases} 1 & \text{if } \exists k \in 1, \ldots, 12 \mid CI_{i,t+k} = 1, \\ 0 & \text{otherwise.} \end{cases}$$

If the reason for the middling explanatory power in our results is the narrow definition of a crisis and the difficulty of predicting the exact timing of such episodes, then this broader definition should improve the inclusion probabilities of our explanatory variables. It should be noticed that in this case we are giving more relevance to the explanatory power for differences between countries, as opposed to within countries.

Analogously to our exercise for the original index, we estimate models within static and a dynamic specification classes using now this transformed crisis index.[12] The results are presented in Tables 5 and 6 .For comparison we again report the intervals of significant parameter values obtained by Bussière (2007).[13]

- Include Tables 5 and 6 about here -

Most of the inclusion probabilities remain well below the prior threshold of 0.5. However, it strikes that in both static regressions the inclusion probabilities have improved dramatically for the real effective exchange rate deviation from a linear trend and for the financial contagion variable. Both variables now have a posterior inclusion probability close to one. Moreover, they both have the expected sign and

[12]Note that the extension of the time window implies a certain information loss. In the dynamic panel in this new setting the dependent variable thus has to be lagged by 12 months.

[13]Note that the comparability is limited in the dynamic setting since we, unlike Bussière, include the stock indices in this specification.

in terms of magnitude come very close to the parameters obtained by Bussière. The same holds true also in the dynamic setting, where, in addition, also the included Datastream stock index (institutions) shows substanitial explanatory abilities.

These results suggest that, while the exact timing of a crisis may indeed be unpredictable, differences in macroeconomic and financial variables still contain information about differential degrees of currency crisis exposure. Moreover, for the probability of a "crisis period" merely two groups of variables seem to matter: the deviation of the real exchange rate from trend on the one hand, and financial market indicators on the other. These results enforce the hypothesis that each currency crisis is eventually triggered by the behavioral change of financial market participants, who seem to care to some extent about a handful of macroeconomic variables and to a great extent about the (herding) behaviour of their collegues.

5 Conclusions

The dominant majority of early warning mechanisms for currency crises employs some version of fundamental-based binary choice models. To our knowledge, none of the papers on the subject tackels the issue of model uncertainty in currency crisis model explicitly. In the present paper we have explicitly taken into account model uncertainty in the framework of a binary choice model. By means of Bayesian model averaging we estimate the coefficients for each variable as weighted averages over the alternative models from the model space, where the weights correspond to the posterior probability of each model. In order to figure out the value added by this approach as opposed to "standard" logit regressions we have used the same data set as one of the most recent studies on the subject by Bussière (2007).

If the discrete dependent variable is constructed so as to predict the exact month in which a crisis may happen our conclusions are twofold. On the one hand, we have found that coefficients mostly have the expected signs coinciding with the benchmark study. On the other hand, however, our principal quality gauge, the posterior inclusion probability (the sum of posterior probabilities of all models containing a particular variable), unveils the lacking robustness of the relationships between regressors and the dependent variable. These results imply that at least in this setting the best model to explain a currency crisis is a mere time and country-unspecific constant. Our results, therefore, indicate that none of the usual macroeconomic fundamental variables is a robust determinant of a currency crisis for the definition and sample used. The results improve considerably if we consider defining "crisis periods" instead of crisis occurrences. Defining crisis periods as observations up to one year prior to the crisis, we find that real exchange rate developments and financial variables are able to robustly explain differences in the probability of a country experiencing such episodes.

Since our sample starts in 1994 it could well be that episodes of currency distress included in the sample are crises rather of the second and third generation type. In such a case it would not be surprising that fundamental data show only limited explanatory power. To turn the argument around, the fundamentals should play a much more significant role in a sample covering the first generation type of crises. Exactly along these paths we are planning to conduct our future research.

A finer way of testing the different theoretical frameworks proposed by the three generations of currency crises models would imply grouping variables by theory and computing the joint inclusion probability of these groups of variables. The construction of groups of variables by theory could be handled in the BMA framework using the proposal by Brock, Durlauf and West (2003) of using a hierarchical prior in order to sort variables into theories or thematic indicators (see also the recent contribution by Doppelhofer and Weeks, 2007, for the concept of jointness of determinants in the BMA framework). Although we did not follow this approach in the paper, we propose it as a potentially fruitful path of further research.

An interesting issue that has not been directly tackled in the paper and that would deserve further scrutiny is the possibility of nonlinear effects in form of interactions among the potential determinants of crises. Developments in some relevant variables may just be responsible for preparing the ground for imbalances that end up a currency crisis when triggered by an unsound development in an additional variable. The use of interaction terms in a BMA setting could assess the importance of this type of effects.

References

[1] Abiad, A. 2003. Early-Warning Systems: A Survey and a Regime-Switching Approach. In: IMF Working Papers, WP/03/32. International Monetary Fund, Washington.

bis Bank for International Settlements 2003. BIS Papers No. 16: Guide to the international banking statistics, Bank of International Settlements, Basel, April 2003.

[2] Brock, W.A., S.N. Durlauf, and K.D. West 2003. Policy Evaluation in Uncertain Economic Environments. In: Brookings Papers on Economic Activity 1, 235-322.

[3] Bussière, M. 2007. Balance of Payment Crises in Emerging Markets - How Early Were the "Early" Warning Signals?. European Central Bank Working Paper 713.

[4] Bussière, M. and M. Fratzscher 2006. Towards a New Early Warning System of Financial Crises. In: Journal of International Money and Finance 25. 953-973.

[5] Chen, C. 2005. How Well can we Predict Currency Crises? Evidence from a Three-Regime Markov-Switching Model. Mimeo, Department of Economics, UC Davis, December.

[6] Crespo Cuaresma, J. and G. Doppelhofer 2007. Nonlinearities in Cross-Country Growth Regressions: A Bayesian Averaging of Thresholds (BAT) Approach. In: Journal of Macroeconomics, 29. 541-554.

[7] Crespo Cuaresma, J. and T. Slacik 2007. Predicting Currency Crises Using the Term Structure of Relative Interest Rates: Case Studies of the Czech Republic and Russia. In: Focus on European Economic Integration 01/07. Oesterreichische Nationalbank.

[8] Doppelhofer, G. and M. Weeks 2007. Jointness of growth determinants. In: Journal of Applied Econometrics, forthcoming.

[9] Fernández, C., Ley, E. and M.F. Steel 2001. Model Uncertainty in Cross-Country Growth Regressions. In: Journal of Applied Econometrics, 16. 563-576.

[10] Flood, R. and Garber, P. 1984, Collapsing Exchange Rate Regimes: Some Linear Examples. In: Journal of International Economics, 17. 1-13.

[11] Frankel, J.A. and A.K. Rose 1996. Currency Crashes in Emerging Markets: an Empirical Treatment. In: Journal of International Economics, 41. 351-366.

[12] Kaminsky, G., Lizondo, S. and Reinhart, C.M. 1998, Leading Indicators of Currency Crises. In: International Monetary Fund Staff Papers, 45. 1-48

[13] Koop, G. 2003. Bayesian Econometrics. Chichester, John Wiley & Sons.

[14] Krugman, P. 1979, A Model of Balance-of-Payment Crisis. In: Journal of Money, Credit and Banking, 11. 311-325

[15] Krugman, P. 1996. Are Currency Crises Self-Fulfilling? In: NBER Macroeconomics Annual 1996. 347-407.

[16] Krugman, P. 1998. What Happened to Asia? Mimeo, Massachussets Institute of Technology.

[17] Leamer, E. E. 1978. Specification Searches. New York, John Wiley & Sons.

[18] Madigan, D. and York, J. 1995. Bayesian Graphical Models for Discrete Data. In: International Statistical Review, 63. 215-232.

[19] Malz, A. M. 2000. Do Implied Volatilities Provide Early Warning of Market Stress? The Risk-Metrics Group, Working Paper No. 00-01.

[20] Obstfeld, M. 1994. The Logic of Currency Crises. In: Cahiers Economiques et Monetaires, 43. 189-213

[21] Peltonen, T. A. 2006. Are Emerging Market Currency Crises Predictable? - A Test. European Central Bank Working Paper 571.

[22] Raftery, A.E. 1995. Bayesian Model Selection in Social Research. In: Sociological Methodology, 25. 111-196.

[23] Sala-i-Martin, X. Doppelhofer, G. and R. Miller 2004. Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. In: American Economic Review, 94. 813-835.

[24] Schwarz, G. 1978. Estimating the Dimension of a Model. In: Annals of Statistics 6. 461-464.

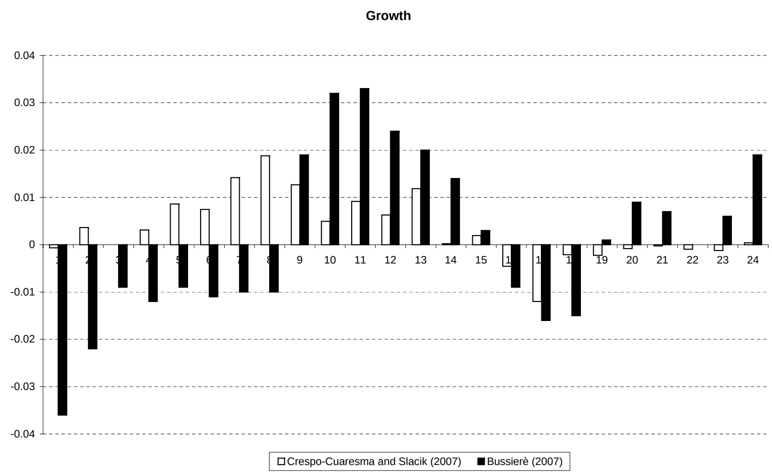

Figure 1: Estimated parameters at different lag lengths

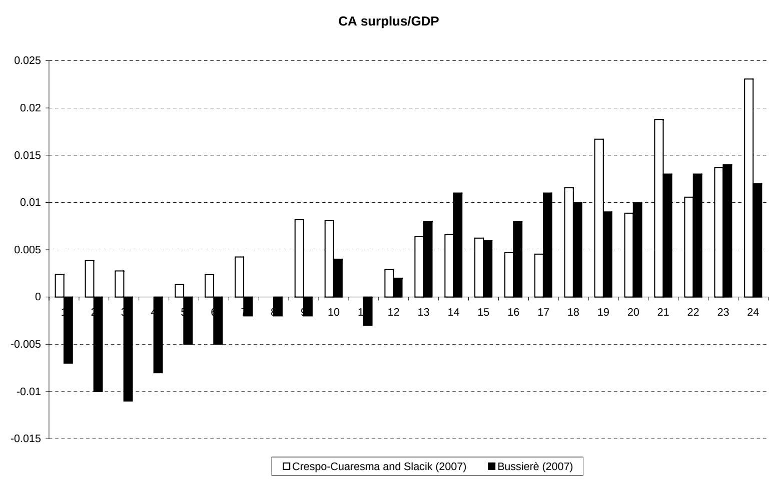

Figure 2: Estimated parameters at different lag lengths

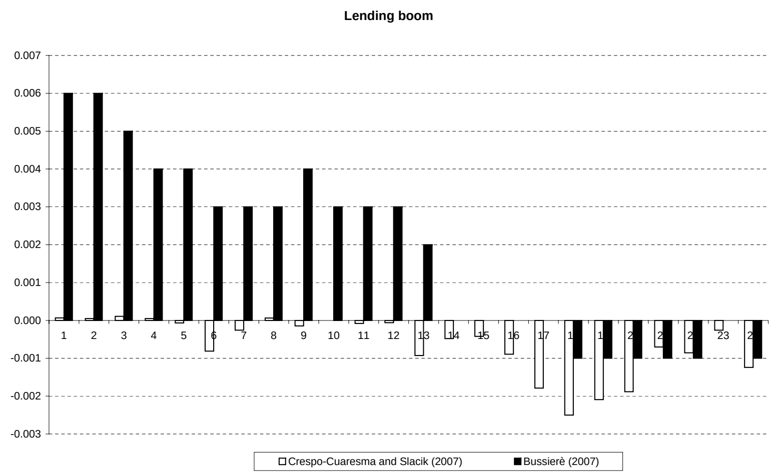

Figure 3: Estimated parameters at different lag lengths

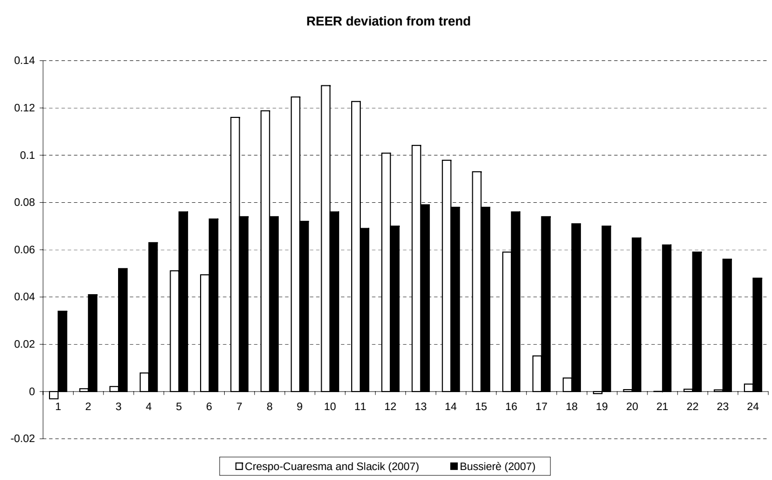

Figure 4: Estimated parameters at different lag lengths

Variable name	**Definition**	**Details**
Exchange rate (trend deviation)	$REERDEV_{i,t} = \frac{REER_{i,t} - Trend_{i,t}}{Trend_{i,t}} * 100$	Trend defined as a simple linear trend
Lending boom	$LB_{i,t} = \left(\frac{CPS_{i,t}}{GDP_{i,t}} - \frac{\overline{CPS}_{i,t-24}}{GDP_{i,t-24}} \right) * 100$	$\frac{\overline{CPS}_{i,t-24}}{GDP_{i,t-24}} = \frac{1}{12} \sum_{k=0}^{11} \frac{CPS_{i,t-24-k}}{GDP_{i,t-24-k}} * 100$;
		$CPS_{i,t}$ = credit to the private sector
Short-term debt/reserves	$STDR_{i,t} = \frac{STD_{i,t}}{RES_{i,t}} * 100$	$STD_{i,t}$ = short term debt;
		$RES_{i,t}$ = international reserves
Total debt/reserves	Analogously to the previous one	Locational or consolidated definition
Current account balance	$\frac{CA_{i,t}}{GDP_{i,t}}$	
Govnernment balance	$\frac{GB_{i,t}}{GDP_{i,t}}$	
Financial contagion	$CONT_{i,t} = \sum_{j=1}^{N-1} EMPI_{i,t} * Correl_{i,j}$	$Correl_{i,j}$ = correlation of equity market returns between country i and country j
Datastream index, total market	12-months percentage change	Broad index
Datastream index, banks	12-months percentage change	Sub-index
Datastream index, financial institutions	12-months percentage change	Sub-index
GDP growth rate	Yearly growth rate of GDP	

Table 1: Basic variables: Definitions

Variable	**Static**		**Static uncorrelated**		**Bussière (2007) static**	
	$E(\beta_i \mid \mathbf{Y})$	Inc. Prob.	$E(\beta_i \mid \mathbf{Y})$	Inc. Prob.	Simple static	Fixed effects
Exchange rate, dev. from trend	0.007658	0.001285	0.021211	0.001445	[0.025; 0.042]	[0.032; 0.045]
Lending boom	0.004109	0.002581	0.008854	0.002312	[0.006]	[0.005; 006]
Short-term debt/reserves	0.000456	0.001335	0.000976	0.001278	[0.003; 0.004]	[0.007; 0.009]
Total debt/reserves (lc)	0.000252	0.001266			[0.002]	[0.004]
Total debt/reserves (cc)	0.000333	0.001701			[0.003]	[0.006]
Current account balance	−0.012997	0.001434	−0.032725	0.001473	*n.s.*	[−0.141; −0.077]
Govnernment balance	0.020414	0.000947	0.048560	0.000945	[0.082]	*n.s.*
Financial contagion	0.023883	0.011678	0.051947	0.009797	[0.043]	[−0.015; 0.043]
Datastream index, total market	−0.002986	0.008047	−0.012907	0.033148	*n.s.*	[−0.008]
Datastream index, banks	−0.003206	0.023155			*n.s.*	[−0.014]
Datastream index, financial institutions	−0.003414	0.029542	−0.011913	0.095018	*n.s.*	[−0.015]
Growth rate	−0.007179	0.000846	−0.014045	0.000838	[−0.052]	*n.s.*

Table 2: BMA results: Static model

Variable	**Dynamic**		**Dynamic uncorrelated**		**Bussière (2007) dynamic**	
	$E(\beta_i\|\mathbf{Y})$	Inc. Prob.	$E(\beta_i\|\mathbf{Y})$	Inc. Prob.	Simple static	Fixed effects
Crisis index, lag 1	0.582846	0.003311	0.584356	0.003343	*n.s.*	*n.s.*
Crisis index, lag 2	0.034475	0.000722	0.037394	0.000722	*n.s.*	*n.s.*
Crisis index, lag 3	0.032963	0.000723	0.036480	0.000723	*n.s.*	*n.s.*
Crisis index, lag 4	0.357034	0.001151	0.359204	0.001157	*n.s.*	*n.s.*
Crisis index, lag 5	0.776955	0.015559	0.778136	0.015779	[1.636; 1.909]	[1.298; 1.615]
Crisis index, lag 6	0.760693	0.014288	0.761846	0.014475	[1.344; 2.036]	[1.229; 2.057]
Exchange rate, dev. from trend	0.007840	0.001315	0.007729	0.001296	[0.037; 0.056]	[0.042; 0.599]
Lending boom	0.004101	0.002564	0.004100	0.002567	*n.s.*	*n.s.*
Short-term debt/reserves	0.000455	0.001331	0.000457	0.001329	[0.003; 0.004]	[0.009; 0.011]
Total debt/reserves (lc)	0.000252	0.001263			[0.0017]	[0.005]
Total debt/reserves (cc)	0.000332	0.001694			[0.003]	[0.007]
Current account balance	−0.013013	0.001436	−0.013017	0.001437	*n.s.*	[−0.082]
Govnernment balance	0.020321	0.000945	0.020402	0.000947	*n.s.*	*n.s.*
Financial contagion	0.023864	0.011573	0.023900	0.011740	*n.s.*	[−0.056; 0.052]
Datastream index, total market	−0.002978	0.007926	−0.002984	0.008090	*n.s.*	*n.s.*
Datastream index, banks	−0.003200	0.022722			[−0.011]	[−0.013]
Datastream index, financial institutions	−0.003408	0.028988	−0.003407	0.029626	[−0.011]	[−0.016]
Growth rate	−0.007056	0.000843	−0.007230	0.000846	*n.s.*	*n.s.*

Table 3: BMA results: Dynamic model

Variable	$E(\beta_i \mid \mathbf{Y})$	**Max. inc. prob.**	**at lag**
Crisis index	0.47073	2.08×10^{-5}	5
Current account balance	0.023066	3.18×10^{-5}	24
Govnernment balance	−0.017251	1.30×10^{-5}	18
Growth rate	0.008615	1.69×10^{-5}	5
Lending boom	−0.000927	1.02×10^{-5}	13
Financial contagion	0.035614	9.55×10^{-5}	5
Datastream index, banks	−0.005556	4.22×10^{-5}	24
Datastream index, financial institutions	−0.005589	6.07×10^{-5}	24
Datastream index, total market	−0.010482	0.000154	24
Exchange rate, dev. from trend	0.129465	0.894149	10
Short-term debt/reserves	0.00066	1.98×10^{-5}	7
Total debt/reserves (cc)	0.000435	3.53×10^{-5}	23
Total debt/reserves (lc)	0.000183	1.93×10^{-5}	22

Table 4: BMA results: Dynamic model with lagged explanatory variables

Variable	**Static**		**Static uncorrelated**		**Bussière (2007) static**	
	E(β_i|**Y**)	Inc. Prob.	E(β_i|**Y**)	Inc. Prob.	Simple static	Fixed effects
Exchange rate, dev. from trend	0.157588	1	0.15754	1	[0.092; 0.104]	[0.100; 0.131]
Lending boom	0.007909	0.044759	0.007805	0.041711	[0.007]	[0.006]
Short term debt/reserves	0.001784	0.010563	0.001018	0.008125	[0.004]	[0.009; 0.012]
Total debt/reserves (lc)	-0.001541	0.003943			*n.s.*	[0.008]
Total debt/reserves (cc)	0.000848	0.016333			[0.005]	[0.013]
Current account surplus	-0.025566	0.005702	-0.025418	0.005445	*n.s.*	[-0.083; -0.061]
Government surplus	-0.047456	0.003069	-0.04733	0.002895	*n.s.*	[0.243]
Financial contagion	0.071689	0.999994	0.071657	1	[0.063; 0.070]	[0.071; 0.084]
Growth rate	-0.025984	0.002907	-0.026202	0.002818	[-0.063; -0.04]	[-0.059; -0.026]

Table 5: BMA results for TCI as dependent variable: Static model

Variable	**Dynamic**		**Dynamic uncorrelated**		**Bussière (2007) dynamic**	
	$E(\beta_i\|\mathbf{Y})$	Inc. Prob.	$E(\beta_i\|\mathbf{Y})$	Inc. Prob.	Simple static	Fixed effects
Lagged dependent variable	-0.40697	0.003468	-0.400762	0.001675	*n.s.*	*n.s.*
Exchange rate, dev. from trend	0.160483	1	0.157799	1	[0.099; 0.109]	[0.103; 0.134]
Lending boom	0.006963	0.016235	0.007558	0.028585	*n.s.*	*n.s.*
Short term debt/reserves	0.00125	0.006489	0.001003	0.007343	[0.004]	[0.009; 0.012]
Total debt/reserves (lc)	-0.000956	0.002355			*n.s.*	[0.008]
Total debt/reserves (cc)	0.000832	0.012289			*n.s.*	[0.013]
Current account surplus	-0.02254	0.003624	-0.024533	0.004854	*n.s.*	[-0.070; -0.081]
Government surplus	-0.064848	0.009033	-0.06368	0.007149	*n.s.*	*n.s.*
Financial contagion	0.062504	0.999167	0.06708	1	[0.061; 0.067]	[0.075; 0.086]
Data stream index, total market	-0.00682	0.031511	-0.007013	0.499063		
Data stream index, banks	-0.005494	0.201715				
Data stream index, institutions	-0.006329	0.737342				
Growth rate	-0.015798	0.001164	-0.026202	0.001412	[-0.052]	[-0.029; -0.039]

Table 6: BMA results for TCI as dependent variable: Dynamic model

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Jesus Crespo Cuaresma and Tomas Slacik

On the determinants of currency crises: The role of model uncertainty

Abstract

We tackle explicitly the issue of model uncertainty in the framework of binary variable models of currency crises. Using Bayesian model averaging techniques, we assess the robustness of the explanatory variables proposed in the recent literature for both static and dynamic models. Our results indicate that the variables belonging to the set of macroeconomic fundamentals proposed by the literature are very fragile determinants of the occurrence of currency crises. The results improve if the crisis index identifies a crisis period (defined as the period up to a year before a crisis) instead of a crisis occurrence. In this setting, the extent of real exchange rate misalignment and financial market indicators appear as robust determinants of crisis periods.

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