Determinants of Currency Crises: A Conflict of Generations?

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Crespo Cuaresma and Slačík (2007) show that macroeconomic fundamentals are rather fragile determinants of currency crises under model uncertainty. The objective of the present follow-up study is to search for empirical support for the first- and second-generation models of currency crises in emerging economies using a larger dataset that includes crisis episodes of the 1980s and 1990s, while explicitly taking into account model uncertainty in a Bayesian manner. In line with the propositions made in the theoretical literature, our results suggest that crisis episodes in the 1980s were driven predominantly by adverse developments of macroeconomic fundamentals, while the results for crises in the 1990s might well be interpreted as empirical support for the second-generation type of crises. In addition, our estimation results stand in contradiction to the popular bipolar view and suggest that de facto intermediate exchange rate arrangements considerably reduce the risk of a speculative currency attack.

1 Introduction

The extensive research on currency crises that has been conducted both on the empirical and the theoretical front over the past three decades is often categorized in first-, second- and third-generation models. Prior to 1990, crises were believed to be driven mainly by unfavorable developments of macroeconomic fundamentals and were therefore thought to be to a large extent predictable. In contrast, the fact that exchange rate turbulences in the 1990s were not really preceded by unsustainable fiscal or monetary policies gave rise to the second-generation model, in which speculative currency attacks are triggered by sudden shifts in investors' expectations. In the *third-generation models*, the next stage of this development, it is the exposure of the financial sector to immanent risks and mismatches that leads to and aggravates currency and banking crises.

In the present paper we ask whether (and if so, to what extent) the model generations for currency crises find support in the data. This piece of research is thus a follow-up and a complementary exercise to Crespo Cuaresma and Slačík (2007), who show that macroeconomic fundamentals are rather fragile determinants of currency crises under model uncertainty. However, since their sample ranges from 1994 to early 2003, it might be conjectured that it covers predominantly currency crises of the second and third generation, in which fundamentals typically play only a secondary role. Hence, in this context the natural question arises whether the impact of macroeconomic fundamentals is more significant in first-generation crisis episodes and whether crisis determinants in earlier periods differ from those of later types of currency attacks. Therefore, we use a sample that covers a time span of more than two decades to assess whether earlier crises were indeed driven predominantly by adverse fundamentals while attacks in the 1990s can be traced back mainly to factors that play a major role in the second- and, partially, third-generation models.

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Given the binary character of the dependent variable – a crisis occurs or does not occur – we employ a limited dependent variable model, as does most of the literature. However, given that the extensive theoretical research does not provide guidelines on the precise set of explanatory variables, there is a substantial level of uncertainty with respect to the choice of covariates. Therefore, while pursuing our objective of assessing the relative importance of the determinants of first- and second-generation currency crises, we explicitly take into account model uncertainty using Bayesian statistical techniques (Bayesian model averaging – BMA). In concrete terms, we average the parameter estimates over alternative models using posterior model probabilities as respective weights to evaluate the relative importance of different variables. As the model space grows exponentially with the number of covariates, at some point it becomes impossible to calculate an average over all existing models within a finite amount of time. Therefore we reduced the intractably large model space and confined ourselves to "relevant" models only. We did this by using a simple Markov chain Monte Carlo model composite (MC^3) algorithm, thanks to which model subspaces with the highest posterior probability are visited.

The remainder of the paper is structured as follows: Section 2 outlines the quintessence of each of the three model generations, which will help us set the stage and interpret the results. Section 3 is devoted to the methodology, focusing in particular on the Bayesian model averaging and the MC algorithm. In section 4 we briefly describe the data and develop some intuition for the variables against the background of the theory developed in section 2. Section 5 presents and discusses the results, while section 6 concludes.

2 Currency Crises: Theoretical Settings

The ground-breaking contributions to the currency crisis literature, now dubbed *first-generation models*, reacted to speculative attacks that swept financial markets, particularly in Latin America in the late 1970s and early 1980s. The pioneering work in this realm, later extended in different aspects, was carried out by Krugman (1979) and Flood and Garber (1984). In these models, the speculative attack on a fixed exchange rate is triggered by an unsustainable fiscal policy. Excessive primary deficits are financed through credit creation by the central bank. The domestic credit expansion implies a predictable drain of international reserves, which would eventually lead to their complete exhaustion and to a devaluation of the exchange rate to the so-called shadow level. The latter is defined as the exchange rate that would prevail if the central bank ran out of foreign reserves and abandoned the peg while at the same time letting domestic credit grow. In other words, the shadow exchange rate is the price of foreign currency that would equilibrate the money market after a speculative attack in which international reserves were exhausted. Under the model assumptions, the shadow exchange rate thus rises linearly at the same rate at which domestic credit grows. This implies that at the very moment at which the shadow exchange rate marginally exceeds the peg, a speculative gain emerges for each unit of foreign reserves purchased from the central bank. Speculators anticipate this development and compete for the profit. However, since there cannot be any profit opportunity in an equilibrium, speculators end up triggering an attack precisely when the shadow exchange rate is equal to the level of the peg and their speculative profit is zero.

Under the strict assumptions of the first-generation models, foreign reserves drop to zero at the time of an attack, money supply falls in line with the size of the attack, and the exchange rate does not move. Moreover, given the assumed interest rate parity, the domestic interest rate has to increase by the size of the expected rate of devaluation. However, if the strict assumptions of a zero-maturity interest rate and perfect foresight are relaxed, the crisis should be preceded by rising longer-term interest rates and leaking reserves. At the time of an attack, the exchange rate will also rise discretely.

Hence, in first-generation models a currency crisis is triggered by financial markets foreseeing an exchange rate devaluation that they deem inevitable, usually due to unsustainable fiscal policy. However, the first-generation models might justify such an expectation also with an adverse development of other fundamentals – e.g. high inflation or money growth, or unsustainable current account deficits – that lead to a deviation of the shadow exchange rate from parity. It should be stressed that in the world of first-generation models no discrete shock is necessary for a speculative attack to occur.

The existing literature provides empirical evidence that the first-generation models are generally well applicable to crises that happened prior to 1990. Given the unfavorable development of fundamentals, those episodes of currency distress were to a great extent predictable. This view, however, was challenged by speculative attacks in the 1990s, particularly by those in the European Exchange Rate Mechanism in 1992, which were not really preceded by undisciplined fiscal and monetary policies. This gave rise to the *second generation of currency crises models* in which government behavior is no longer modeled to be state invariant. Hence, it is no longer assumed that the government is exogenously committed to the fixed peg. They rather maximize an objective function, which apart from the fixed exchange rate policy contains other, possibly conflicting, target variables (see e.g. Obstfeld, 1994).

Second-generation models thus generally exhibit multiple equilibria and, even if the economy is at a no-attack equilibrium, a speculative run may suddenly occur as a consequence of self-fulfilling expectations. Hence, even if there are capital gain opportunities known to the financial markets, they might not be pursued by speculators and the country may remain in the no-attack equilibrium. The smaller and less coordinated the market participants are, the more likely it is that this scenario will occur.

Different mechanisms have been proposed in the literature for the self-fulfilling shift from the no-crisis to the crisis equilibrium. Morris and Shin (1995) show that if an uncertainty element is introduced into the information signal the agents receive about the state of the economy, only the crisis equilibrium remains. In their model, a speculator's assessment of other investors' interpretations of the incoming announcements plays a crucial role in the outbreak of a crisis. Conversely, for example in Banerjee (1992), it is not an investor's concern about the beliefs of others that triggers a crisis but his observation of others' actual behavior that might make him join the herd even against his own positive signal. In this model, agents are thus apt to follow the crowd rather than use their own information and lean against the wind. Yet another viewpoint is presented in Calvo and Mendoza (1997), who show that the likelihood of herding behavior increases with the globalization of capital markets. The more intertwined the world financial markets are, the more the relative performance of fund managers matters. Consequently, they tend to pick similar portfolios and are less inclined to search for and process country specific information that may be outside of the mainstream.

The fact that some of the currency crises at the end of the 1990s coincided with turbulences in the financial sector inspired a further development in the currency crises literature. In these *third-generation models* the exposures of the financial sector to immanent currency, liquidity and credit risks lead to and aggravate currency and banking crises (see Burnside, Eichenbaum and Rebelo 2007).[3]

In empirical work, one would expect that in crisis episodes to which the first-generation models are supposed to apply, particularly fundamental variables should show up with a strong impact on the probability of crisis occurrence. Apart from variables capturing the fiscal stance financed by domestic credit, a significant effect on the probability of a crisis might thus be expected from, inter alia, the current account, high inflation or money growth episodes, or real interest rate hikes (which typically precede crises in this model cohort). In contrast, in the second-generation type of crises we will be particularly interested in the effect of variables that approximate the market sentiment stimulating herding behavior. If crises of the third type were at play, then variables which unearth weaknesses and mismatches in the financial sector should prove significant.

3 Methodology

Given the lack of an unambiguous theoretical framework that would uniquely determine which variables are to be chosen in an equation attempting to explain currency crises, we do not know either the true model or a clearly defined subset of all possible models from which the true model has to be recruited. Hence, we face a substantial level of model uncertainty that has to be taken into account if we do not want to implicitly impose a rather strong restriction by presuming to know a limited model space in which the true model has to be included. Yang (2004), for instance, compares hypothesis testing and model selection strategies both theoretically and empirically and concludes that "when model selection rules give very different answers, model combining is a better alternative approach for estimation and prediction. With a proper weighting, the large variability of the estimator from model selection can be substantially reduced."

A way to combine models with a proper weighting is the Bayesian Model Averaging (BMA) methodology, which was employed and described in detail in Crespo Cuaresma and Slačík (2007) and references therein. In a nutshell, the BMA algorithm proposes averaging parameter estimates over all alternative models using posterior model probabilities as respective weights. Hence, the posterior mean and variance of the parameters of interest can be used to make inferences on the quantitative effect of changes in the covariates on the probability of a currency crisis explicitly taking into account the existence of model uncertainty. In the

[3] *Some studies refer to a fourth generation of currency crises although it seems that no consensual definition of this latest generation has been reached. While Krugman (2003) talks about a more general financial crisis model in which other asset prices play the starring role, Shimpaleea and Boucher Breuer (2005) define the fourth generation as models in which currency crises are determined by institutional factors. In contrast, Ghosh (2002b) understands the fourth generation as those models in which currency crises are created and accentuated by unforeseeable financial panic from different players in the market and the government.*

same fashion, we can evaluate posterior inclusion probabilities for the different variables proposed, which can be obtained by summing the posterior probability of models containing each individual variable (or groups of it). This measure thus captures 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.

However, since the model space grows exponentially with the number of regressors (2^K, where K is the number of potential regressors), at some point it is not computationally feasible to calculate an average of the parameter values over all models in the model space. For cases where the cardinality of the model space makes the problem intractable, several methods have been proposed for approximating the posterior model probability. We will use a simple Markov chain Monte Carlo model composite (MC^3) algorithm to evaluate the posterior distribution based on the work of Madigan and York (1995) (see also Fernández et al., 2001, and Koop, 2003). The random walk chain Metropolis-Hastings algorithm is implemented in the model space as follows. In a given replication r of the algorithm, a candidate model M^{r+1} is proposed, which is randomly drawn from the neighborhood of the current model, (M^r). The neighborhood is composed by the model which is active in that replication, (M^r), 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

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

which is just the Bayes factor comparing M^r and M^{r+1} if equal prior probability is assumed across models (as will be the case in the empirical application below). Such a diffuse prior over the model space is a natural choice if we do not want to impose a prior structure which gives a higher weight to certain model sizes or combinations of variables, although other priors based on anchoring the prior to the expected model size (Sala-i-Martin et al., 2004) or imposing beta-binomial structures (Ley and Steel, 2007) have been recently proposed in the literature. This algorithm is repeated many times, and the posterior mean, variance and inclusion probability as described above are computed for the group of models replicated, which will tend to cover model subspaces with the highest posterior probability.

4 Data and Variables

In our study we will assess the robustness of different variables as predictors of currency crises. As we are interested in the probability of currency crises in emerging economies, we employed the to our best knowledge longest and most comprehensive dataset[4] consisting of a panel of monthly observations for 24 emerging economies: Argentina, Brazil, Chile, Colombia, the Czech Republic, Ecuador, Egypt, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Morocco, Peru, the Philippines, Poland, Russia, Slovakia, South Africa, Thailand, Turkey

[4] *For a detailed description of the data and their original sources, see Peltonen (2006), to whom we are very grateful for sharing his dataset with us.*

and Venezuela. Due to the limited availability of data for some variables, the dataset covers a timespan from January 1980 to December 2001, so that the adjusted sample contains a maximum of 3,340 country-month observations. It should be noted that for some countries, especially post-communist economies, not all data are available for the 1980s.[5] Since none of the variables used in the study can be directly interpreted as capturing the key elements behind third-generation models, we will focus on the first two model generations while taking model uncertainty explicitly into account. In order to empirically verify the adequacy of first- and second-generation models in subperiods of the data, we will also consider two subsamples ranging from January 1980 to December 1989 and from January 1990 to December 2001, respectively.

In line with the literature, the dependent crisis variable is constructed in two steps. First we compute a continuous variable known as the exchange market pressure index *(EMPI)*. Although there is no uniform definition, typically the EMPI is a weighted average of the change of the nominal or real exchange rate, the country's foreign reserves and the real or nominal interest rate.

We construct the *EMPI* for country *i* at time *t* as

$$EMPI_{i,t} = \omega_{ER}\left(\frac{\Delta e_{i,t}}{e_{i,t-1}}\right) + \omega_r\left(\frac{\Delta ir}{ir_{i,t-1}}\right) - \omega_{res}\left(\frac{\Delta res_{i,t}}{res_{i,t-1}}\right), \tag{1}$$

where e stands for the price of a U.S. dollar in country i's currency, ir is the difference of short-term interest rate in country i and in the U.S.A., and res is the level of international reserves. As weights, the precision (inverse of the variance) for each one of these variables is used. In the next bout, this continuous variable is transformed into a binary index which equals 1 whenever $EMPI_{i,t}$ exceeds the threshold of the country-specific mean ($\overline{EMPI_i}$) plus twice its standard deviation σ_{EMPI_i},

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

The choice of independent variables is inspired by the earlier literature which we briefly reviewed in section 2. Table 1 lists the set of regressors which are used as potential explanatory variables and table 2 presents descriptive statistics for the dependent and independent variables. Financial crises can typically not be reduced to only a few explanatory variables; they are complex events characterized by an accumulation of multiple economic problems. Naturally, this complexity cannot be mirrored in the three model generations which try to pinpoint the most distinguishing features. Hence, a clear-cut clustering of the explanatory variables into the generation categories is barely possible, although some variables can be expected to emerge as significant, with a higher probability in one generation type of crisis than another. 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. However, it provides no information about a possible trend

[5] *Hence, as communist countries are in fact not included in the 1980s subsample due to the missing data, the results are not really affected by their inclusion. Estimates for a subsample excluding these countries are available from the authors upon request.*

appreciation of the real exchange rate prior to a crisis as was observed in some studies (e.g. Edwards, 1989). Annual GDP growth is included, since higher economic growth should reduce the government's temptation to devalue its currency, e.g. in order to gain competitiveness. The effect of this variable should thus be particularly strong in the second-generation type of crises. 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. Since a rise of this indicator, which renders a crisis more likely, can stem either from a rise in debt or a fall in reserves, we would expect this variable to be particularly significant in first-generation crisis episodes. Unfortunately, the data for these two variables were not available for the 1980s. The current account and government balances normalized with the respective country's GDP are typical fundamentals that play an important role in the framework of first-generation models. The contagion dummy could capture either an adverse development of fundamentals in the region or herding behavior on the finanical markets. Since Bussière and Fratscher (2006) show that contagion accross countries is only significant via the financial channel and not via trade, this variable should probably be significant particularly in second-generation crises. The exchange rate regime dummies will uncover whether some arrangements are more prone than others to currency crises. According to an influential, so-called "bipolar," view represented e.g. by Fischer (2001) since the beginning of the 1990s, countries have tended to leave the intermediate exchange rate regimes, which are perceived as more vulnerable, in favor of extreme arrangements such as free floating, dollarization/euroization or monetary unions. In contrast, Frankel (1999) presents a more sceptical approach to this issue and Rogoff et al. (2003) provide evidence for the bipolar view being a fallacy. In their opinion, there is neither support for countries moving toward the polar exchange rate arrangements nor for the claim that

Table 1

Definition of Independent Variables

Variable	Definition
Real exchange rate misalignment	Deviation of the real effective exchange rate from a Hodrick-Prescott trend
GDP growth rate	Annualized growth rate of GDP
Short-term debt	Short-term debt relative to reserves
Total debt	Total debt relative to reserves
Current account balance	Current account balance relative to GDP
Government balance	Primary fiscal balance relative to GDP
Contagion	Dummy equal to 1 if there has been a currency crisis within 3 months in the same region
De facto pegged FX regime	Dummy as defined by Reinhart and Rogoff (2004)
De facto crawling peg FX regime	Dummy as defined by Reinhart and Rogoff (2004)
De facto managed float FX regime	Dummy as defined by Reinhart and Rogoff (2004)
De facto floating FX regime	Dummy as defined by Reinhart and Rogoff (2004)
De facto freely falling FX regime	Dummy as defined by Reinhart and Rogoff (2004)
Real interest rates	Short term nominal interest rates deflated by the CPI
Broad money/reserves	Annualized growth rate of the ratio of broad money to reserves
Domestic credit	Annualized growth rate of real domestic credit
Stock market	Annualized growth of the composite stock market index
Hyperinflation	Dummy equal to 1 if annual CPI inflation > 40%

Source: Authors.

Table 2

Descriptive Statistics: Independent Variables

	Crisis variable	Real exchange rate misalignment	GDP growth rate	Short-term debt	Total debt	Current account balance	Government balance	Contagion	De facto pegged FX regime
Mean	0.029	−0.001	0.034	0.939	1.987	−0.020	−0.030	0.006	0.125
Median	0.000	−0.001	0.040	0.578	1.327	−0.020	−0.024	0.000	0.000
Maximum	1.000	0.738	0.403	15.695	27.043	0.183	0.100	1.000	1.000
Minimum	0.000	−0.542	−0.465	0.091	0.193	−0.209	−0.267	0.000	0.000
Standard deviation	0.168	0.069	0.052	1.262	2.424	0.047	0.039	0.078	0.331
Observations	5657	6418	6096	3934	3934	6012	5568	7200	6336

Source: Authors' calculations.

Table 2 continued

Descriptive Statistics: Independent Variables

	De facto crawling peg FX regime	De facto managed float FX regime	De facto floating FX regime	De facto freely falling FX regime	Real interest rates	Broad money/ reserves	Domestic credit	Stock market	Hyper-inflation
Mean	0.278	0.271	0.027	0.191	0.291	3213.342	14525035.000	1655.181	0.163
Median	0.000	0.000	0.000	0.000	0.019	0.021	0.050	0.174	0.000
Maximum	1.000	1.000	1.000	1.000	1388.455	182*105	$793000*10^{5}$	5912571.000	1.000
Minimum	0.000	0.000	0.000	0.000	−163.730	−1.000	−1.000	−1.000	0.000
Standard deviation	0.448	0.444	0.162	0.393	22.414	232163.300	10700*105	82671.930	0.370
Observations	6336	6336	6336	6336	6108	6155	5460	5778	7200

Source: Authors' calculations.

the latter outperform intermediate regimes. Due to the recognized inconsistencies between reported and actual policies in many countries, we employ both the de jure exchange rate regimes as defined by the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions as well as two widely acknowledged de facto classifications compiled by, respectively, Reinhart and Rogoff (2004) and Levy-Yeyati (2005). Real interest rates, domestic credit growth, the hyperinflation dummy and the ratio of broad money to reserves are typical first-generation fundamentals which should affect the probability of a crisis. In contrast, the stock market variable is a proxy for financial market sentiment and is expected to matter particularly in crisis episodes of the second generation.

5 Empirical Results: Robust Determinants of Currency Crises

The results of the Bayesian Model Averaging exercise are presented in table 3. The potential determinants correspond to all the variables in table 1 for samples including the 1990s, and all except *total debt* and *short-term debt* for the exercise using data from the 1980s (due to lack of data on these variables for that decade). We assumed equal prior probability for all models, which implies prior inclusion probabilities of 50% for each covariate. Therefore, in table 3 we report the posterior inclusion probabilities for each variable and the posterior expected value of the corresponding parameter for those variables with inclusion probabilities over 0.5. Also presented is the ratio of the posterior expected value of the parameter to the root of the posterior variance of the parameter, which can be interpreted as a measure of precision in the estimates analogous to the t-ratio in classical (frequentist) econometrics.[6] We will refer to these variables as "robust" (since, after observing the data, the inclusion probability increases), although robustness should also be measured in terms of the precision of the corresponding estimated parameter and is hence discussed below. We used an MC^3 algorithm such as the one described above to obtain the results, with 10,000 replications.[7] All explanatory variables are evaluated with a one month lag with respect to the crisis variable, which is defined as in (1)-(2). The lag is used in an attempt to proxy a causality structure from the independent variables to the crisis indicator and avoid (at least to a certain extent) endogeneity. Results are presented for the full sample and for the 1990s and 1980s.

The full sample results highlight three variables as the most important determinants of currency crises: the *GDP growth rate,* the *current account balance* and *real interest rates,* which achieve posterior inclusion probabilities of over 99%. The effect of these variables is not estimated very precisely, although the posterior mean of the parameters has the expected sign in all three cases. Interestingly, the variables found to be robust determinants can be interpreted as representative of both first-generation and second-generation models. In particular, the current account balance and real interest rates can be seen as typical representative variables relevant for crisis prediction in first-generation models. GDP growth can be thought of as a first-generation determinant to the extent that it reflects fundamental macroeconomic dynamics, although it can also be interpreted as a second-generation model variable since it affects the temptation to devalue.

The results emmanating from the division in subsamples show fundamental differences across decades. The growth rate of GDP is the only robust covariate for the 1990s. For this subsample, the BMA estimate is much more precise and has a similar expected value to the one obtained for the whole sample. This implies that the lack of precision in the estimation of the effect of GDP growth on the probability of currency crisis occurrences for the full sample is caused by the lack of relationship in the 1980s (see corresponding column in table 3). Hence, GDP growth thus seems to be rather a second-generation model variable which reduces the incentive of the government to abandon the exchange rate peg. The other two variables which were found to be robust in the full sample, the current account balance and real interest rates, appear to be relevant only in the 1980s. Moreover, if we exclusively use data for this decade, their effects are more precisely estimated and have the expected sign: smaller current account deficits (or higher surpluses) reduce the probability of a crisis and higher real interest rates imply a higher

[6] *If there are 2^K models, 2^{K-1} contain each particular covariate, so that our prior inclusion probability is given by $\frac{2^{K-1}}{2^K}$.*

[7] *We also obtained the exact results (with model averaging based on the estimation of the posterior for the full model space) in some cases, so as to evaluate the precision of the Markov Chain proposed. Our results (available upon request) indicate that 5,000 replications already lead to quantitatively very similar results to those obtained from the exact method.*

crisis probability. For the subsample spanning the 1980s, we also find evidence that countries undergoing hyperinflationary episodes tended to have a much higher probability of a currency crisis. This effect, however, is not present in the 1990s and does not show up robustly if we use data for the full period. The results may thus be interpreted as in line with the propositions made by the theoretical literature. Surprisingly enough, however, we do not find any robust impact of typical first-generation fundamental variables such as the government balance, domestic credit growth or the ratio of money supply to reserves in any of the samples. There might be several interpretations for this nonresult. To begin with, the first model generation was developed particularly in reaction to pervasive currency turmoil in the 1970s and early 1980s. Currency markets calmed down somewhat in the mid- and late 1980s. Hence, a subsample spanning the 1980s might not be ideal for finding a significant effect of typical first-generation model variables. Moreover, Kaminsky and Reinhart (1999) document that while the ratios of domestic credit to GDP and M2 to reserves grow soundly prior to the crisis, the former stabilizes and the latter even falls shortly before the crisis. Since we use one-month lags of these indicators, they might not capture the rising trend and in the future, research of longer lags should be included. Similarly, the same authors show that the fiscal balance to GDP fares worst among the macroeconomic indicators in accurately calling a currency crisis. Lastly, Fidrmuc (2003) shows that, particularly in the 1980s, current account deficits tended to be accompanied by fiscal deficits. In our 1980s subsample, the correlation between the two variables for crisis episodes is around 0.5, suggesting a nonnegligible degree of multicollinearity. In order to test this hypothesis explicitly, we also repeated the exercise without the current account variable. With this constellation of variables, the fiscal deficit variable appears as a robust determinant of currency crises, with an inclusion probability of 0.99. Interestingly enough, the nature of the exchange rate regime does not affect the probability of a crisis. While the reported results were derived using the de facto categorization by Reinhart and Rogoff (2004), neither of the two alternatively employed classifications – the de jure exchange rate regimes as defined by the IMF and the de facto classification compiled by Levy-Yeyati (2005) – changed the outcome.

In order to test the robustness of the result concerning the lack of predictive power of the fiscal variable, we also carried out the exercise including up to one year (12 months) lagged fiscal deficits. That is, we expanded the model set to include 11 new variables, each one corresponding to a lag of the primary fiscal balance relative to GDP. The inclusion probabilities for the fiscal variables, however, were in all cases below 10%. Their inclusion did not affect the evidence concerning the effect of other variables on the probability of a currency crisis.

The binary crisis variable used until now is given by the definition in (1)-(2). A model based on such a crisis definition attempts to predict the exact timing of a crisis in a given country. However, it is argued in Bussière (2007) that, by trying to explain the exact month of a crisis, the model attempts to achieve something that may simply be unfeasible. Moreover, such a definition might identify multiple crisis episodes which in fact are part of the same crisis. To avoid these problems, we follow Peltonen (2006) and smooth the crisis variable by switching a noncrisis observation to a crisis observation if two out of the three neighboring periods were labeled as crisis months.

Table 3

Bayesian Model Averaging Results: Definition (Equation 2) of Crisis Moments

	Full sample			1990s			1980s		
	PIP	$E(\beta\|Y)$	$\frac{E(\beta\|Y)}{\sqrt{var(\beta\|Y)}}$	PIP	$E(\beta\|Y)$	$\frac{E(\beta\|Y)}{\sqrt{var(\beta\|Y)}}$	PIP	$E(\beta\|Y)$	$\frac{E(\beta\|Y)}{\sqrt{var(\beta\|Y)}}$
Real exchange rate misalignment	<0.5	–	–	<0.5	–	–	<0.5	–	–
GDP growth rate	0.9999	−4.6029	0.4353	0.9999	−4.0929	−5.7659	<0.5	–	–
Short-term debt	–	–	–	<0.5	–	–	–	–	–
Total debt	–	–	–	<0.5	–	–	–	–	–
Current account balance	0.9983	−5.0870	1.1659	<0.5	–	–	0.9313	−9.1725	−2.9218
Government balance	<0.5	–	–	<0.5	–	–	<0.5	–	–
Contagion	<0.5	–	–	<0.5	–	–	<0.5	–	–
De facto pegged FX regime	<0.5	–	–	<0.5	–	–	<0.5	–	–
De facto crawling peg FX regime	<0.5	–	–	<0.5	–	–	<0.5	–	–
De facto managed float FX regime	<0.5	–	–	<0.5	–	–	<0.5	–	–
De facto floating FX regime	<0.5	–	–	<0.5	–	–	<0.5	–	–
Real interest rates	0.9999	0.0176	0.0000	<0.5	–	–	0.9022	0.0404	1.9788
Broad money/reserves	<0.5	–	–	<0.5	–	–	<0.5	–	–
Domestic credit	<0.5	–	–	<0.5	–	–	<0.5	–	–
Stock market	<0.5	–	–	<0.5	–	–	<0.5	–	–
Hyperinflation	<0.5	–	–	<0.5	–	–	0.8985	0.7571	2.4242

Source: Authors' calculations.

Note: PIP stands for Posterior Inclusion Probability. Results obtained using 10,000 replications of the Markov chain Monte Carlo model composite procedure explained in the text. Since our prior inclusion probability is given by 0.5, we report the posterior inclusion probabilities for each variable and the posterior expected value of the corresponding parameter only for those variables with inclusion probabilities over this threshold.

We redo the BMA exercise for this variable proxying "crisis periods" instead of "crisis moments" and summarize the results in table 4, which has the same structure as table 3. The results of this exercise confirm and complement those highlighted above for crisis moments. Our conclusions concerning the robustness of the GDP growth rate, current account balance and real interest rates as predictors of the currency crises for the whole sample are left unaffected by the use of the alternative crisis definition. This time, however, the estimation precision of these three covariates in the whole sample has improved substantially. An interesting feature which is revealed in the new estimates is that differences in exchange rate regimes did not systematically account for crises in the 1980s but played an important role in explaining different exposure to currency crises in the 1990s and were also strong enough in the whole sample. Moreover, in contrast to the bipolar view, it turns out that intermediate exchange rate regimes (peg, crawling peg and managed float) substantially decrease the probability of a crisis. This result is in line with earlier studies and should be interpreted with respect to the reference regime (which is not included in the procedure), which is the free-falling exchange rate regime defined by Reinhart and Rogoff (2004) for observations corresponding to inflation episodes over 40%. While Rogoff et al. (2003) document that the impact of de facto exchange rate regimes on the probability of a currency crisis is mixed and substantially hinges on the definition of the dependent variable, the time span covered and the countries included in the sample, Ghosh, Gulde and Wolf (2002a) conclude that, statistically, currency crises are more likely under floating regimes, but their impact is more severe under pegged and intermediate

Table 4

Bayesian Model Averaging Results: Definition of Crisis Periods

	Full sample			1990s			1980s		
	PIP	$E(\beta\|Y)$	$\frac{E(\beta\|Y)}{\sqrt{var(\beta\|Y)}}$	PIP	$E(\beta\|Y)$	$\frac{E(\beta\|Y)}{\sqrt{var(\beta\|Y)}}$	PIP	$E(\beta\|Y)$	$\frac{E(\beta\|Y)}{\sqrt{var(\beta\|Y)}}$
Real exchange rate misalignment	<0.5	–	–	<0.5	–	–	<0.5	–	–
GDP growth rate	0.9990	−3.3972	−5.0023	0.9990	−3.8535	−4.7846	<0.5	–	–
Short-term debt	–	–	–	<0.5	–	–	–	–	–
Total debt	–	–	–	<0.5	–	–	–	–	–
Current account balance	0.9998	−5.4405	−5.2117	<0.5	–	–	0.8703	−9.0364	−2.3060
Government balance	<0.5	–	–	<0.5	–	–	<0.5	–	–
Contagion	<0.5	–	–	<0.5	–	–	<0.5	–	–
De facto pegged FX regime	0.9999	−0.8508	−5.0950	1.0000	−0.9848	−4.9012	<0.5	–	–
De facto crawling peg FX regime	0.9999	−0.7259	−5.9078	1.0000	−0.7397	−5.0432	<0.5	–	–
De facto managed float FX regime	0.9999	−0.7662	−6.0684	1.0000	−0.8816	−6.1146	<0.5	–	–
De facto floating FX regime	<0.5	–	–	<0.5	–	–	<0.5	–	–
Real interest rates	0.9981	0.0146	2.9658	<0.5	–	–	0.8518	0.0403	1.7392
Broad money/reserves	<0.5	–	–	<0.5	–	–	<0.5	–	–
Domestic credit	<0.5	–	–	<0.5	–	–	<0.5	–	–
Stock market	<0.5	–	–	0.9998	−0.0749	−2.8709	<0.5	–	–
Hyperinflation	<0.5	–	–	<0.5	–	–	0.8705	0.8277	2.2379

Source: Authors' calculations.

Note: PIP stands for Posterior Inclusion Probability. Results obtained using 10,000 replications of the Markov chain Monte Carlo model composite procedure explained in the text. Since our prior inclusion probability is given by 0.5, we report the posterior inclusion probabilities for each variable and the posterior expected value of the corresponding parameter only for those variables with inclusion probabilities over this threshold.

regimes.[8] Finally, the results for the newly defined currency crises also unveil one new determinant which was not labeled as robust under the former definition. High stock market returns tended to relate to a lower probability of crisis over the course of the 1990s, a result which can be easily reconciled with second-generation models if interpreted as a proxy for market sentiment.

Our use of monthly data has an effect on the nature of the determinants of currency crises. In particular, there could be variables whose short-term volatility obscures a causal effect that may be present at lower frequencies. In order to unveil such relationships, we repeated the exercise after aggregating the data at a quarterly frequency. Our crisis variable now takes value one if there was at least one month in the quarter where the monthly indicator signaled a crisis. The results for the crisis "moments" definition (2) are presented in table 5 and reveal some interesting relationships. On the one hand, GDP growth remains a robust determinant of currency crises, with a similar elasticity to that obtained with monthly data. On the other hand, real exchange rate misalignments appear as an empirically relevant determinant of the occurrence of crises. The information embodied in this variable is hence lost when moving to higher frequencies but appears statistically important at the quarterly frequency. The opposite occurs to current account

[8] *We also repeated the exercise using de jure classifications. De jure exchange rate regimes did not appear robustly related to the occurrence of crises in this setting, although their inclusion tended to affect the robustness of other variables. Further research in this direction should be carried out in order to unveil the nature of the interaction between de jure regimes and macroeconomic fundamentals as determinants of crisis periods.*

Table 5

Bayesian Model Averaging Results: Definition (Equation 2) of Crisis Moments – Quarterly Data

	Full sample		
	PIP	$E(\beta\|Y)$	$\frac{E(\beta\|Y)}{\sqrt{var(\beta\|Y)}}$
Real exchange rate misalignment	0.9999	4.8503	6.0862
GDP growth rate	0.9999	−5.6262	−5.4856
Short-term debt	–	–	–
Total debt	–	–	–
Current account balance	<0.5	−1.3086	−0.5712
Government balance	<0.5	–	–
Contagion	<0.5	–	–
De facto pegged FX regime	<0.5	–	–
De facto crawling peg FX regime	<0.5	–	–
De facto managed float FX regime	<0.5	–	–
De facto floating FX regime	<0.5	–	–
Real interest rates	<0.5	–	–
Broad money/reserves	<0.5	–	–
Domestic credit	<0.5	–	–
Stock market	<0.5	–	–
Hyperinflation	<0.5	0.0077	0.0032

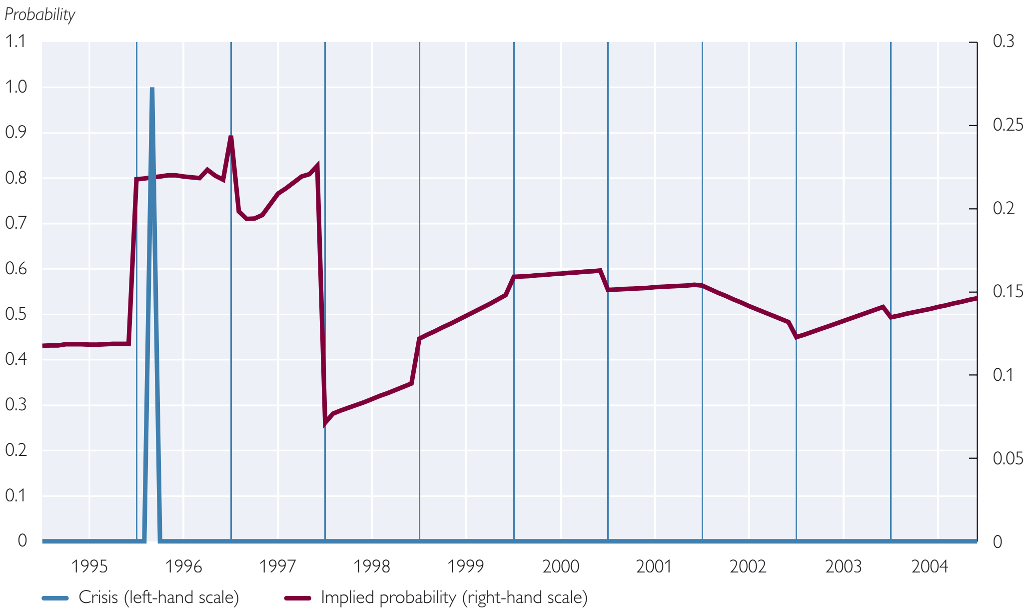
Source: Authors' calculations.

Note: PIP stands for Posterior Inclusion Probability. Results obtained using 10,000 replications of the Markov chain Monte Carlo model composite procedure explained in the text.

dynamics and real interest rates, whose high(er) frequency component contains more important information concerning potential crisis situations in the exchange rate market. This result may be interpreted as evidence that the signals issued by

Chart 1

Implied Out-of-Sample Crisis Probability for Bulgaria



Source: Authors' calculations.

some variables tend to be masked at higher frequencies through noisy volatility, which is averaged away when aggregating the variable at lower frequencies. However, the opposite, namely that short-run volatility may also contain useful signals, occurs for some other variables.

As an extra robustness check concerning the out-of-sample abilities of the model averaging estimates, we also applied the Bayesian model-averaged parameters of the robust variables to data to Bulgaria, which is not part of the sample used for estimation. The definition of the crisis is given by (2). Chart 1 presents the implied probabilities and the observed crisis in the available sample. The probability implied by the averaged parameters increases sharply and doubles right before the crisis, implying a reasonable out-of-sample predictive power of the Bayesian averaged model.

6 Conclusions

The objective of the present paper is to complement the results obtained in Crespo Cuaresma and Slačík (2007) by searching for empirical support for the three model generations in which the literature on financial crises is usually categorized. In this sense, this exercise is both a follow-up and a complementary exercise to that carried out in Crespo Cuaresma and Slačík (2007). We use a broad sample of 24 emerging economies and, due to the limited availability of data, we concentrate on the first and second generation type of crises. In contrast to the existing literature on early warning mechanisms for currency crisis, which generally ignores the immanent caveat of model uncertainty, we took this issue explicitly into account by means of the Bayesian model averaging algorithm. We thus calculated the parameter value for each covariate as a weighted average over all relevant models using posterior model probablities as respective weights. We employed the Markov chain Monte Carlo model composite algorithm to reduce the size of the large model space.

In line with the propositions made by the theoretical literature, the results suggest that crisis episodes in the 1980s were driven predominantly by an adverse development of macroeconomic fundamentals. Particularly hyperinflation, high interest rates and current account deficits tended to increase the probability of a crisis. Results for the subsample covering the 1990s could be interpreted as an empirical indication for the second-generation type of crises. In contrast, surprisingly enough, other fundamental variables that typically play a major role in theoretical first-generation concepts, such as government balance or domestic credit growth, seem to have no robust impact on crisis probabilities. If the definition of the dependent crisis variable is broadened from one month to a time window of three months, the impact of de facto exchange rate regimes becomes robust too. In this respect, the results stand in contradiction to the popular bipolar view and suggest that intermediate exchange rate arrangements considerably reduce the risk of a speculative currency attack.

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