The Role of Bank and Corporate Balance Sheets on Early Warning Systems of Currency Crises—An Empirical Study [§]

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Abstract

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This study analyzes the role of bank and corporate balance sheets on early warning systems (EWS) of currency crises. Using firm-level data on debt structure, leverage, liquidity, and profitability, this study presents estimations of EWS for a panel of emerging markets. Using calibration experiments, we assess the performance of alternative EWS specifications in a comprehensive range of crisis-probability cut-offs. These models supplement EWS based on traditional macroeconomic indicators, improving forecasting performance substantially. The results support the third-generation models of currency crises, and can assist policymakers on the design of surveillance strategies tailored for heterogeneous levels of risk tolerance and country specificities.

Keywords: Early warning systems, external vulnerability, currency crises, balance sheet effects, emerging markets

JEL classification: F31, F47, G15

1. Introduction

Despite significant macroeconomic progress over the last decade, a series of unexpected and severe financial crises during the 1990s devastated standards of living in emerging market economies worldwide. These episodes constituted the empirical basis for the development of theoretical models, which came to be known as "third-generation" models, aiming at explaining the unprecedented nature of these crises.[1] These features motivated the development of early warning systems (EWS) that timely identify vulnerabilities underlying the incidence of currency crises.

The third-generation models of currency crises explore aspects other than traditional macroeconomic fundamentals at the root of the turmoil in emerging markets. For instance, in the late 1990s the Asian crisis countries did not display the classic macroeconomic vulnerabilities that had characterized previous currency crises. Third-generation models point to the involvement of the private sector and balance sheet vulnerabilities as core causes of these crisis episodes. This literature has focused on sectoral and aggregate balance sheet weaknesses, such as excessive indebtedness (leverage), currency mismatches, maturity mismatches (illiquidity), and

[1] Three different stages can be identified in the currency crisis literature. First-generation models address currency crises during the 1970s and 1980s, and attribute them to expansionary domestic credit, unsustainable fiscal deficits and inadequate international reserves. Second-generation models assign the early 1990s crises to the political costs of maintaining fixed exchange rates. In other words, investors perceived that, among the potential equilibria, governments would give up exchange rate control to help domestic indebted private sector and alleviate unemployment rates. This shattered markets confidence and accelerated the attacks to the currency. The third-generation models are the focus of the present work. See, for example, Claessens and Kose (2013).

low profitability.[2] While some of these models have focused on weaknesses on the corporate sector—e.g. Krugman (1999), Bris and Koskinen (2002), Aghion, Bacchetta, and Banerjee (2004), and Schneider and Tornell (2004)—other models have focused on the financial sector (banks)—e.g. Chang and Velasco (2000, 2001), Jeanne and Wyplosz (2003), and Burnside, Eichenbaum, and Rebelo (2004). The latter approach contributes toward understanding the role of financial sector problems—and their spillovers to other sectors—in the run up to a currency crisis.

Still, there seems to be limited empirical work examining the role of the private sector in crisis episodes. On the one hand, there are few contributions on the corporate side: for example, Davis and Stone (2004) study the impact of financial crises on aggregate corporate funding and expenditure. On the other hand, most of the studies on the financial sector performance (e.g., Demirguc-Kunt and Detragiache, 2000) are related with banking crisis episodes, which may have different sources and momentum than currency crises. An early attempt to link banking problems to currency crises (in the context of twin crises) was made by Kaminsky and Reinhart (1999), although without the use of balance sheet indicators.

Moreover, the empirical studies about EWS often cited in the literature have not incorporated firm-level information, either from the corporate or the financial sectors, on the assessment of external vulnerability—e.g. Kaminsky, Lizondo, and Reinhart (1998), Berg and Pattillo (1999), Berg, Borensztein, Milesi-Ferretti, and Pattillo (1999), Berg, Borensztein, and Pattillo (2005), and Bussière and Fratzscher (2006). Renewed interest on crises leading indicators arose with the global financial crisis, as highlighted in e.g. Blanchard, Das, and Faruqee (2010), Claessens, Dell'Ariccia, Igan, and Laeven (2010), Lane and Milesi-Ferretti

[2] See, for example, Allen, Rosenberg, Keller, Setser, and Roubini (2002).

(2011), Rose and Spiegel (2011), Berkmen, Gelos, Rennhack, and Walsh (2012), and Frankel and Saravelos (2012). To the best of our knowledge, the first EWS that includes corporate sector indicators was provided by Mulder, Perrelli, and Rocha (2012). Nevertheless, the role of banks' balance sheets on EWS of currency crises remains to be analyzed.

In the present work, we develop EWS that incorporate banks' balance sheet indicators in econometric models that estimate the probability of currency crisis episodes in emerging market economies. Together with a country's macroeconomic position, legal environment (corporate governance), and corporate balance sheets, the information from banks' balance sheets are shown to be strong leading indicators of external vulnerability. We focus on balance sheet measures of debt structure, financial leverage, liquidity, and profitability, studying their contribution to the likelihood of currency crisis episodes. These complement, rather than substitute, traditional macroeconomic indicators of external vulnerability.

Furthermore, through the use of calibration experiments, we analyze the out-of-sample performance of each model, in addition to the in-sample results, and compare it with prominent EWS that use a comparable methodology but do not capture balance sheet effects. We also provide an analysis of the EWS performance across a range of surveillance strategies that vary according to the risk tolerance of the policymaker. Our findings suggest that banks' balance sheet indicators improve substantially the predictive power of EWS.

This paper aims to explain the core period of events that motivated the third generation models of currency crisis in the economic literature. Hence it tries to draw lessons from a well-defined class of historical crisis episodes. As such, the scope of the paper covers the 1990s and early 2000s and focuses on the Asian crisis. Our study is, to the best of our knowledge, the first EWS to use micro balance sheet data from the banking sector in the design of EWS for emerging

markets. One of the main lessons from our paper is that the health of bank and corporate balance sheets is critical to detect and prevent currency crises. From a policy perspective, this is of the utmost importance for the purpose of timely identification of vulnerabilities aiming at crisis prevention.

The paper is organized as follows. In Section 2 we describe the indicators considered here. Section 3 describes the sample and explains the estimation techniques required to assess the probabilities of crisis across countries. In Section 4 we show the in-sample estimates, calibrate the models and compare their performances; and in Section 5 we provide a similar analysis for the out-of-sample results. Finally, Section 6 presents concluding remarks.

2. Searching for Potential Crisis Indicators

The traditional EWS literature relies on a set of core macroeconomic variables, as suggested by seminal work of Berg and Pattillo (1999) and Berg, Borensztein, Milesi-Ferretti, and Pattillo (1999). The latter study finds real effective exchange rate overvaluation, large current account deficit over GDP, slow reserves growth, high ratio of short-term debt to reserves, and low exports growth to increase the probability of a currency crisis. We also include these variables in our model.

In the spirit of third-generation models, Mulder, Perrelli, and Rocha (2012) extend this basic EWS to include a set of corporate balance sheet indicators of external vulnerability. These are grouped in four different categories: debt structure, financial leverage, liquidity, and profitability. In light of the third-generation models we expect the weakening of debt structure and leverage variables to contribute positively to the likelihood of crises, while the improvement on liquidity and profitability to reduce external vulnerability. The market microstructure effects

that increase the probability of a crisis may be amplified by the business environment in which corporations operate, and by the involvement of the public sector with corporate and bank problems. The sources of such amplification shocks are hard to identify, but macroeconomic balance sheet information may be useful in the assessment of countries vulnerability. To capture this, that study also includes a set of macro balance sheet and legal indicators in the EWS.

The present paper contributes to the literature by considering financial sector leading indicators, with a focus on the role of banks' balance sheets on the probability of currency crises. The idea behind the financial sector leading indicators we propose is analogous to that of the corporate sector, with each variable being calculated for the financial corporations. We examine a set of debt structure, leverage, liquidity, and profitability ratios for companies included in the financial sector. Some of the variables used (e.g., Total Debt over Common Equity) can be calculated for both corporate and financial sectors, but others (e.g., Total Loans over Total Deposits) are specific to the banking sector. As suggested by third-generation models we expect debt structure and leverage variables to increase countries external vulnerability, while liquidity and profitability ratios to reduce the likelihood of crises. We control for interaction effects through the use of composite variables, in which every corporate indicator is multiplied by the country's ratio of domestic credit to the private sector and non-financial public enterprises over GDP—this provides a measure of the impact of the corporate sector through the banking sector. The Appendix presents a detailed list of these financial sector indicators.

3. Econometric Methodology and Model Selection Criteria

3.1. Data

Our sample comprises 19 emerging market economies, spanning the period 1991 through 2001. This comprises the core period of events that the third generation models of currency crises aim to explain. The list of countries was selected on the basis of banking and corporate balance sheet data availability, and it is close to the ones used by the most established studies designing early warning systems for currency crises—notably Kaminsky, Lizondo and Reinhart (1998) (hereafter KLR) and Berg and Pattillo (1999) (hereafter BP).[3] Using the Worldscope database, we collected data on all available non-financial corporations' and banks' balance sheets for the countries in the sample, from which we construct economic indicators at the individual company level.[4] For the macro balance sheet indicators we use data from the Bank for International Settlements.[5]

3.2. Methodology

[3] The countries included are: Argentina, Brazil, Chile, Colombia, Egypt, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, South Africa, Thailand, Turkey, and Venezuela. The sample includes crisis and non-crisis countries.

[4] We take the median (rather than average) for each year and country in order to limit the risk of data pollution from the presence of outliers and misreports.

[5] We also use data from IMF-IFS and IMF-WEO. We transform the annual balance sheet data and the quarterly macro indicators into a monthly frequency by replicating the last value along the following months until a new observation is available (this represents the information available to the markets until a new observation is obtained at the end of the next year).

The econometric methodology we adopt follows that of Berg and Pattillo (1999) and Berg, Borensztein, Milesi-Ferretti, and Pattillo (1999). The authors propose the use of generalized linear Probit models to detect leading indicators of currency crises. In those models, the dependent variable is a dummy assuming the value of 1 under the presence of a crisis and zero otherwise. To assess a crisis ahead of time, the dependent variable assumes the unit value 24 months before crisis episodes.[6] Their explanatory variables are a set of macroeconomic indicators reflecting the status of the real effective exchange rate, the current account balance, international reserves growth, the short-term external debt to international reserves ratio, and exports growth. They transform the values for these indicators into percentiles for each variable. The use of percentiles establishes thresholds for each series, which enables the distinction between usual and unusual values for those series, especially important when working with such a distinct sample of countries.[7]

The first model we estimate includes the macroeconomic indicators used in Berg and Pattillo (1999), hereafter called EWSi group (we call this model EWS reduced sample).[8] To this, we add four different groups of economic indicators that reflect the market micro foundations of the corporate sector (CS_i group) and of the financial sector (FS_i group), the macro balance sheet and institutional environment (MB_i group), and the corporate governance and legal environment

[6] A crisis is defined as occurring when the weighted average of monthly depreciations in the exchange rate and monthly declines in reserves exceeds by more than 3 standard deviations the country mean—the weights are calculated in order to equalize the variance of the two components of the index (Berg and Pattillo, 1999).

[7] They use historical data from 1970 to 1995 for each country. In the present paper we compute percentiles using all available data in our sample.

[8] Thanks to the kind provision of the data by the authors, we could reproduce the results of their original paper, with only minor differences related to data updates and differences in time and country coverage.

(LEG_i group).[9] This process generates a set of five different equations that we estimate as shown below:

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \varepsilon_{tr} \quad (1)$$

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \sum_i \varphi_i p(CS_{it})_r + \varepsilon_{tr} \quad (2)$$

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \sum_i \gamma_i p(FS_{it})_r + \varepsilon_{tr} \quad (3)$$

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \sum_i \omega_i p(MB_{it})_r + \varepsilon_{tr} \quad (4)$$

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \sum_i \lambda_i LEG_{ir} + \varepsilon_{tr} \quad (5)$$

Here Pr(CC=1|t=T) is the time-t probability of a currency crisis in the next 24 months. The subscript *r* indicates each country, *p* indicates the percentiles of the variables, and the subscript *i* indicates the variables included in the models.[10] The system of equations above helps us to develop an economic selection criterion, and the most significant variables will comprise the final versions of the models we estimate:

Corporate balance sheet model (CBS)

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \sum_i \varphi_i p(CS_i) + \sum_i \omega_i p(MB_i)_r + \varepsilon_{tr} \quad (6)$$

Bank and corporate balance sheet model (BBS)

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \sum_i \varphi_i p(CS_i) + \sum_i \omega_i p(MB_i)_r + \sum_i \gamma_i p(FS_i)_r + \varepsilon_{tr} \quad (7)$$

Extended balance sheet model (EBS)

[9] We obtain the legal indicators from La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998).

[10] For simplicity, we use the same subscript for each set of variables, no matter the extent to which the number of variables varies across models.

$$\Pr(CC=1|t=T)_r = \sum_i \beta_i p(EWS_{it})_r + \sum_i \varphi_i p(CS_i) + \sum_i \omega_i p(MB_i)_r + \sum_i \gamma_i p(FS_i)_r + \sum_i \lambda_i LEG_{ir} + \varepsilon_{tr} \quad (8)$$

We propose three versions of augmented early warning systems. The first version (CBS, Eq. (6)) considers the best EWS variables (EWS_i group) plus the most promising corporate (CS_i) and macro balance sheet (MB_i) indicators. The motivation for the CBS model is that, while corporate and macro balance sheet indicators are well developed and reasonably disclosed around the world, financial sector data at a firm-level basis is still being improved in emerging markets. The second version of the models (BBS, Eq. (7)) adds the financial sector indicators (FS_i) to the previous model. This constitutes the BBS model, which main goal is to provide the best time-varying leading indicators of currency crises. Finally, we also include the legal/corporate governance indicators (LEG_i) to the set of potential indicators, giving rise to the third version of the models (EBS, Eq. (8)). The EBS version offers a proxy to the country-specific effects by the use of the time-fixed LEG_i variables. All equations are estimated using a pooled probit regression, as in Berg and Pattillo (1999).

3.3. Selection Criteria

The model selection criterion is primarily based on the economic theoretical background. We expect that the debt structure variables present a positive sign, which means that, for example, the higher the weight of the short-term debt with respect to the total debt (or working capital), the higher the probability of crisis in the coming months. The financial leverage variables are also expected to present a positive sign, because the more leveraged a firm is, the higher the probability of default. Liquidity and profitability indicators should contribute negatively to the likelihood of crisis, given that high liquidity and ratio of returns reduce the economic

vulnerability of companies. Finally, corporate governance indicators were constructed in order to present a negative sign as well, given that the higher the indices of shareholders' rights and contract enforcement, the lower the probability of crisis in a given country. Any variable that presented the wrong sign in a given round of the model selection was discarded at that round, and then "re-tested" in the final model. We also based our selection in statistical significance and information criteria.

4. Econometric Results

4.1. Model Selection

The first combination we estimate is the traditional EWS model proposed by Berg and Patillo (1999). We find that one of the five variables in the core equation, namely exports growth, is not statistically significant in our sample. We therefore eliminate this variable and re-estimate the model. The results are shown in column 1 of Table 1 below. The model offers a goodness-of-fit measure of about 25%. We then add each set of variables discussed above (columns 2-5) corresponding to the equations 2-5, based on the selection criteria.

We then estimate the corporate balance sheet (CBS) model, where the selected variables are the ratio of total debt to common equity (corporate leverage), the ratio of short-term debt to working capital (corporate debt structure), the ratio of corporate debt to total debt (macro debt structure), and the ratio of corporate debt to exports (macro liquidity). The performance of CBS corporate balance sheet model is superior to the core EWS, with a lower value for the information criteria and a higher adjusted R-squared (about 38%) (Table 1, column 6).

Then we undertake a BBS model selection (Table 1, column 7). The list of selected variables includes the ratio of total debt to common equity (both corporate and financial leverages), the ratio of short-term debt to working capital (corporate debt structure), the ratio of short-term debt to long-term debt (financial debt structure), the ratio of total debt over common equity multiplied by the domestic credit to private sector and non-financial public enterprises over GDP (composite corporate leverage), the ratio of corporate debt to total debt (macro debt structure), the ratio of bank debt total debt (macro debt structure), and the ratio of bank and corporate debt to exports (macro liquidity). The BBS model presents an outstanding performance, with goodness-of-fit around 48%, and very low bias and variance (information criteria).

Table 1: Probit Estimations of External Crisis Probabilities (1991 to 2001) a/ b/

	Sign	EWS Reduced Sample (1)		Partial Models EWS & Corporate (2)		EWS & Financial (3)		EWS & Macro B/I (4)		EWS & Legal (5)		Selected Models CBS (6)		BBS (7)		EBS (8)	
Macro Benchmark																	
REER	+	0.018	(10.81)	0.020	(10.22)	0.030	(9.54)	0.020	(11.26)	0.017	(10.07)	0.022	(10.01)	0.032	(8.68)	0.031	(8.05)
CA/GDP	+	0.007	(4.62)	0.009	(5.17)	0.004	(1.62)	0.003	(1.70)	0.009	(5.48)	0.005	(2.83)	0.005	(1.89)	0.007	(2.93)
RGR	+	0.004	(2.68)	0.001	(0.78)	0.006	(3.16)	0.004	(2.17)	0.003	(1.55)			0.006	(2.49)	0.006	(2.46)
STD/R	+	0.024	(13.95)	0.023	(11.90)	0.024	(8.96)	0.020	(10.63)	0.025	(13.80)	0.022	(11.28)	0.022	(7.75)	0.021	(7.62)
Corporate																	
FlevBV	+			0.008	(3.41)							0.016	(10.18)	0.007	(2.33)	0.014	(6.74)
STD/WC	+			0.007	(4.32)							0.005	(2.94)	0.009	(4.11)	0.009	(4.55)
FlevBV*Bnk	+			0.010	(3.93)									0.007	(2.32)		
Financial																	
FlevBV	+					0.012	(6.54)							0.011	(5.81)	0.012	(5.98)
STD/LTD	+					0.004	(2.23)							0.008	(3.85)	0.006	(2.98)
InvLoan/Dep	+					0.014	(6.96)										
Macro-Balance/Institutional																	
CorpD/TotD	-							-0.009	(-5.49)			-0.018	(-9.25)	-0.009	(-4.47)	-0.006	(-2.90)
BankD/TotD	+													0.004	(1.87)	0.003	(1.63)
PubD/TotD	+							0.004	(2.34)								
CorpD/X	+											0.021	(9.98)				
BkCorpD/X	+							0.017	(9.29)					0.017	(7.59)	0.016	(7.66)
BnkCred/GDP	+							0.004	(2.76)								
Legal																	
ShareRight	-									-0.270	(-9.43)					-0.230	(-7.08)
EnforcIndex	-															-0.131	(-2.81)
Constant		-3.649	(-22.01)	-4.915	(-23.73)	-5.991	(-14.90)	-4.282	(-15.54)	-2.968	(-16.78)	-4.748	(-20.28)	-7.383	(-13.29)	-6.053	(-10.05)
Statistics																	
Log Likelihood		-724.65		-619.90		-452.51		-655.07		-683.97		-565.82		-416.448		-398.97	
Akaike Criterion		0.69		0.66		0.54		0.63		0.65		0.61		0.48		0.46	
Schwartz Criterion		0.70		0.69		0.56		0.65		0.66		0.63		0.52		0.50	
McFadden R-squared		0.25		0.32		0.41		0.32		0.29		0.38		0.48		0.50	
Crisis Periods (A)		356		354		283		356		356		354		295		295	
Tranquil Periods (B)		1772		1542		1433		1755		1772		1542		1493		1493	
Sample Size (A+B)		2128		1896		1716		2111		2128		1896		1788		1788	

a/ Heteroskedasticity-consistent QML (Huber/White) z-statistics in brackets.
b/ Type I error probasbility of 1% corresponds to z-statistics of about 2.57, 5% to 1.96, and 10% to 1.64.
REER (Real effective exchange rate), CA/GDP (Current account over GDP), RGR (Changes in reserves), STD/R (Short-term debt over reserves), Corporate FlevBV (Total Debt/Common Equity (Book Value)), STD/WC (Short-term Debt/Working Capital), FlevBV*Bnk (FlevBV multiplied by Domestic Credit to the Private Sector and Non-financial Public Enterprises as a percentage of GDP), Financial FlevBV (Total Debt/Common Equity (Book Value)), STD/LTD (Short-term Debt/Long-term Debt), InvLoan/Dep (Invested Assets and Loans/Total Deposits), CorpD/TotD (Corporate Sector Debt to Foreign Banks/ Total Debt to Foreign Banks), BankD/TotD (Financial Sector Debt to Foreign Banks/ Total Debt to Foreign Banks), PubD/TotD (Public Sector Debt to Foreign Banks / Total Debt to Foreign Banks), CorpD/X (Corporate Sector Debt to Foreign Banks/ Exports), BkCorpD/X (Corporate and Financial Sectors Debt to Foreign Banks/ Exports), BnkCred/GDP (Claims on the Private Sector and Non-Financial Public Enterprises / GDP), ShareRight (Index of shareholders' rights), EnforcIndex (Index of contract enforcement level).

Finally, we estimate the EBS model. Relative to the BBS, it drops the corporate composite leverage variable and adds the shareholders' rights and the contract enforcement indices. The EBS model presents the highest goodness-of-fit (50%) and the lowest Akaike and Schwarz criteria among all tested models (Table 1, column 8).

The improvement of the balance sheet models over the core EWS equation is reflected in a progressive reduction of bias and variance (information criteria) and an increase of the goodness-of-fit as we add the balance sheet indicators to the core EWS equation.

4.2. Crisis Probabilities Right Before the Asian Crisis

To illustrate the economic meaning of these models, we present in Table 2 a summary of the estimated crisis probabilities and countries rank for six different models (KLR, BP, EWS, CBS, BBS, EBS) of early warning systems right before the Asian crisis. We compare those numbers with the actual crisis index and the actual crisis ranks, corresponding to the weighted average of percentage changes in the exchange rate and reserves per country.

The results confirm the high correlation between the actual ranking position across countries and the crisis ranks estimated by our balance sheet models. For example, the Pearson correlation coefficient between the balance sheet models and the actual crisis index is around 80%, while the KLR and BP models present correlation coefficients around 40%. Moreover, all balance sheet models are successful in identifying which countries are in the top-four group in the actual crisis index (i.e. Thailand, Korea, Indonesia, and Malaysia). The CBS and the EBS models present the highest goodness-of-fit in explaining the crisis ranks, with the EBS version matching the positions of Thailand (1^{st}), Indonesia (3^{rd}), Philippines (6^{th}), Turkey (8^{th}), and Mexico (15^{th}). In the same table we also show the average of crisis probabilities according to countries geographical clusters, and show that the probability of crisis in Asian countries was much higher than in any other part of the world right before the crisis episodes.

Table 2: 24 Months Crisis Probabilities for Various EWS Specifications as of June 1997

Country d/	KLR b/		BP c/		EWS Reduced Sample		CBS		BBS		EBS		Actual	
	Prob	Rank	Prob	Rank	Prob	Rank	Prob	Rank	Prob	Rank	Prob	Rank	Crisis Index a/	Rank
Thailand	12%	14	38%	1	89%	1	100%	1	100%	1	100%	1	10.19	1
Korea	25%	3	26%	7	52%	3	57%	4	66%	4	67%	4	9.52	2
Indonesia	11%	15	26%	7	39%	6	72%	3	71%	3	84%	3	4.48	3
Malaysia	17%	6	38%	1	87%	2	98%	2	99%	2	97%	2	4.42	4
Colombia	17%	7	36%	4	51%	5	34%	6	37%	7	31%	7	3.01	5
Philippines	41%	1	22%	11	34%	7	44%	5	54%	5	52%	6	2.68	6
Brazil	37%	2	25%	9	28%	8	31%	7	52%	6	55%	5	0.82	7
Turkey	17%	5	14%	15	14%	9	5%	11	4%	11	9%	8	0.65	8
Venezuela	14%	11	9%	17	3%	16	1%	14	0%	15	0%	14	0.62	9
Pakistan	15%	8	28%	5	52%	4	14%	8	11%	8	8%	9	0.57	10
South Africa	22%	4	23%	10	2%	17	2%	13	0%	14	0%	17	0.52	11
Jordan	14%	13	21%	12	3%	14	NA	NA	NA	NA	NA	NA	0.45	12
India	11%	17	14%	15	1%	18	1%	15	0%	16	0%	16	0.39	13
Chile	11%	15	18%	13	6%	12	12%	9	5%	10	1%	12	0.24	14
Argentina	15%	10	15%	14	6%	11	0%	16	1%	13	2%	11	0.15	15
Mexico	14%	11	6%	18	5%	13	0%	17	0%	17	0%	15	0.15	15
Peru	15%	9	27%	6	7%	10	4%	12	8%	9	5%	10	0.12	17
Israel	11%	17	37%	3	3%	15	10%	10	2%	12	1%	13	-0.11	18
Crisis Probabilities: Averages														
Unweighted Average	18%		24%		27%		29%		30%		30%			
Asian Average	20%		27%		50%		62%		65%		67%			
Latin-American Average	18%		19%		15%		12%		15%		14%			
Others Average	16%		25%		15%		8%		4%		4%			
Crisis Ranks: Estimated vs. Actual														
Linear Regression (R-squared)		0.15		0.16		0.55		0.64		0.59		0.63		
Pearson Correlation Coefficient		0.39		0.40		0.74		0.80		0.77		0.80		

a/ As reported in BP (1999, Table 5), the KLR crisis index corresponds to the weighted average of percentage changes in the exchange rate and reserves. BP provides a Normal standardized version of the index ((actual value-mean)/standard deviation). In their scale, values above 3 correspond to crisis episodes.
b/ The probabilities of Kaminsky, Lizondo, and Reinhart original specification are as reported in BP (1999, Table 5), divided by 100. The ranks above reported correspond to countries' classification within the reduced sample considered here.
c/ The probabilities are reported as in Berg and Patillo (1999), linear model (Table 5). The ranks above reported correspond to countries' classification within the reduced sample considered here.
d/ Egypt was excluded due to lack of data.

4.3. In-Sample Accuracy of Crisis Probabilities

We examine the in-sample predictability power of currency crisis episodes 24 months ahead of time and compare the proposed balance sheet models performance with the KLR and BP models, and the reduced sample EWS model. The results are shown in Table 3. Line A presents the

percentage of correct calls, i.e. the number of times the model emits a signal[11] and there is a crisis, plus the number of times the equation does not emit any signal and there is a tranquil period. According to this criterion, our balance sheet models are superior to the other specifications, with an average number of correct calls (and correct silences) of about 90% at the highest cut-off probability, and 85% at the lowest cut-off probability.

Table 3: In-Sample Accuracy of Crisis Probabilities for the Next 24 Months for Various EWS Specifications

		KLR e/	BP f/	EWS Reduced Sample	CBS	BBS	EBS
Cut-off Probability of 50%							
A	Total Correctly Called Observations a/	82%	84%	86%	88%	90%	91%
B	Pre-crisis Periods Correctly Called b/	9%	7%	31%	52%	58%	61%
C	Tranquil Periods Correctly Called c/	98%	100%	97%	96%	96%	96%
D	False Alarms d/	44%	11%	30%	25%	24%	23%
E	Efficiency Measure = B-D	**-35%**	**-4%**	**2%**	**26%**	**34%**	**38%**
Cut-off Probability of 25%							
A	Total Correctly Called Observations a/	77%	78%	79%	82%	87%	87%
B	Pre-crisis Periods Correctly Called b/	41%	48%	56%	76%	80%	81%
C	Tranquil Periods Correctly Called c/	85%	84%	84%	84%	88%	88%
D	False Alarms d/	63%	63%	58%	49%	44%	42%
E	Efficiency Measure = B-D	**-22%**	**-15%**	**-2%**	**27%**	**36%**	**39%**

a/ As percentage of the total number of observations. There are two situations in which the observation is correctly called: (i) when the crisis probability exceeds the cut-off point, and a crisis happens in the next 24 months, or (ii) when the crisis probability does not exceed the cut-off point, and no crisis happens in the next 24 months.

b/ As percentage of the total number of actual crisis. A crisis is correctly called when situation (i) of note a/ happens.

c/ As percentage of the total number of tranquil periods. A tranquil period is correctly called when the situation (ii) of note a/ happens.

d/ As percentage of the total number of alarms. A false alarm occurs when the estimated crisis probability exceeds the cut-off probability (i.e., alarm) but no crisis ensues in the next 24 months.

e/ Kaminsky, Lizondo, and Reinhart original specification as reported in BP (1999, Table 2).

f/ As reported in Berg and Patillo (1999), linear model (Table 2). This model uses reserves over broad money rather than reserves over short-term debt used in the benchmark model reported in Berg et. al. (1999).

[11] A signal is emitted every time the fitted value surpasses a suggested cut-off value. For example, with a cut-off of 50%, any time the estimated probability of crisis is higher than 50%, a signal is emitted; otherwise, the model is "silent", indicating that it is a tranquil period.

We check pre-crisis times correctly called, and verify that the balance sheet models have on average correctly called 57% of the crisis at the highest cut-off probability, and 79% of the crisis at the lowest cut-off, while the other models were at least 20 percentage points below (with KLR and BP distinctively below). The third aspect to consider is the number of tranquil periods correctly called. Here the models are technically tied, because at the highest cut-offs the balance sheet models are inferior up to 4%, but at the lowest cut-offs—more commonly used in crises prediction—the balance sheet models are superior up to 4%.

We also verify the number of false alarms. A false alarm occurs anytime the model emits a signal, but no crisis happens (i.e., the fitted value is higher than the suggested cut-off, but no crisis ensues in that period). This item is specifically important to avoid self-fulfilling behavior of early warning systems—a common criticism to rating agencies in emerging markets (e.g. Mulder and Perrelli, 2001)—and the catalytic role of capital flights during financial turmoil periods. The balance sheet models are more efficient than any other model at the lowest cut-off level, and only inferior to the BP model at the highest cut-off level.

4.4. Calibration Experiment 1: Choice of Cut-off Levels and Risk Tolerance Levels (In-Sample)

The choice of cut-off levels to prevent currency crisis is generally arbitrary, and the relative performance of any model can vary substantially among the different choices for the cut-off probabilities. Therefore, the evaluation of early warning systems should be done through the

assessment of their performance along an entire range of cut-off points, in order to affirm which of the systems are admissible, which are inadmissible, and which are preferable to others.[12]

Another aspect to be considered is what should be a fair measure of efficiency. In this context, the policymaker will decide how to weigh each of the four virtues: the highest number of correct calls, the highest number of pre-crisis correctly called, the highest number of tranquil periods correctly called, or the lowest number of false alarms.

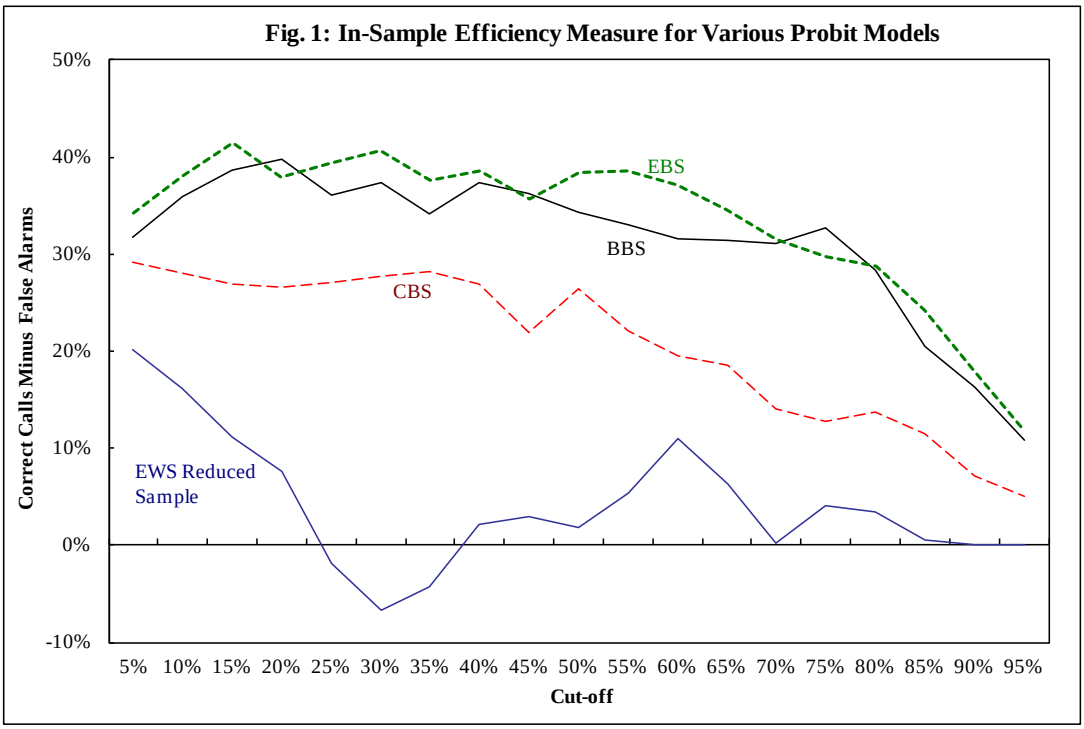
We first suggest a simple measure of efficiency based on the difference between the number of pre-crisis correctly called and the number of false alarms (see Table 3, line E). In this way, the higher the pre-crisis correctly called or the lower the number of false alarms, the higher that difference would be and the better the model. In this sense, we verify that at the 50% cut-off the balance sheet models present efficiency measure ranging from 26% to 38%, and at the 25% cut-off this measure ranges from 27% to 39%. Comparing these results with the performance of the other models one can see that the balance sheet models present a much higher value for that statistic. But is this true for all cut-off points?

In order to answer this question, we re-calculate the performance of four of the six models (EWS, CBS, BBS, EBS)[13], and show the results graphically in Figure 1. From the plot we can see that the EWS specification is an inadmissible estimator, given that there is another estimator superior to EWS at every cut-off. The CBS is also inadmissible, but superior to EWS. Both BBS and EBS are admissible, but none is preferred to each other for all cut-offs. Therefore,

[12] In Bayesian theory, an estimator is inadmissible when there is any other estimator preferable to that one at each point of the support set. See Bickel and Doksum (1977) for more details.

[13] We could not evaluate the performance of KLR and BP original models in other cut-offs as they only provide results for 25% and 50%.

based on the proposed efficiency measure of pre-crisis correctly called minus false alarms, one could choose BBS or EBS model without much concern.



We now propose different measures of efficiency, depending on the goals of the policymaker. The first strategy is the zero tolerance of false alarms (i.e., for each model, the policymaker chooses the lowest cut-off value for which no false alarms are issued). The second strategy is the zero tolerance of crisis not called (i.e., for each model the policymaker chooses the highest cut-off that assures 100% of pre-crisis correctly called). The third option is to select the cut-off probability that offers the highest number of pre-crisis correctly called minus false alarms. The fourth strategy is a simplistic threshold adoption of at most 30% of false alarms (i.e., the policymaker will choose the lowest cut-off up to the point in which 30% of false alarms are ensued). The final strategy is a simplistic threshold in which at least 70% of pre-crisis periods are

correctly called (i.e., the policymaker will choose the highest cut-off such that a minimum of 70% of crisis is correctly called).

Those five suggestions of policy design will help policymakers not only to select a model, but also to use the most appropriate cut-off point for each model. The main results of the experiment are presented in Table 4. To summarize, we verify that the balance sheet models are always superior to the EWS specification for each of these strategies, again based on the gains of pre-crisis correctly called minus false alarms (line E). CBS is inferior to BBS and EBS, but superior to EWS. BBS is inferior to EBS in the third and fifth strategies, but is superior in the first strategy and equally desirable in the second and fourth strategies, considering the criterion of the difference between crises correctly called and false alarms.

Table 4: In-Sample Performance - Calibration of Cut-off Levels and Design of Optimal Strategy

	EWS Reduced Sample	CBS	BBS	EBS
Strategy 1: Zero Tolerance of False Alarms	(Cut-off 76%)	(Cut-off 92%)	(Cut-off 88%)	(Cut-off 91%)
A Total Correctly Called Observations a/	84%	83%	87%	86%
B Pre-crisis Periods Correctly Called b/	6%	8%	19%	17%
C Tranquil Periods Correctly Called c/	100%	100%	100%	100%
D False Alarms d/	0%	0%	0%	0%
E Efficiency Measure = B-D	**6%**	**8%**	**19%**	**17%**
Strategy 2: Zero Tolerance of Crisis Not Called	(Cut-off 2%)	(Cut-off 1%)	(Cut-off 1%)	(Cut-off 1%)
A Total Correctly Called Observations	37%	44%	56%	57%
B Pre-crisis Periods Correctly Called	100%	100%	99%	99%
C Tranquil Periods Correctly Called	24%	31%	48%	49%
D False Alarms	79%	75%	73%	73%
E Efficiency Measure = B-D	**21%**	**25%**	**26%**	**26%**
Strategy 3: Highest B-D	(Cut-off 3%)	(Cut-off 7%)	(Cut-off 19%)	(Cut-off 28%)
A Total Correctly Called Observations	41%	66%	85%	89%
B Pre-crisis Periods Correctly Called	99%	96%	87%	80%
C Tranquil Periods Correctly Called	29%	59%	85%	90%
D False Alarms	78%	65%	47%	38%
E Efficiency Measure = B-D	**21%**	**32%**	**40%**	**42%**
Strategy 4: At most 30% of False Alarms	(Cut-off 50%)	(Cut-off 48%)	(Cut-off 39%)	(Cut-off 41%)
A Total Correctly Called Observations	86%	87%	90%	90%
B Pre-crisis Periods Correctly Called	31%	54%	68%	68%
C Tranquil Periods Correctly Called	97%	95%	94%	94%
D False Alarms	30%	30%	30%	30%
E Efficiency Measure = B-D	**2%**	**24%**	**37%**	**37%**
Strategy 5: At Least 70% of Crisis Called	(Cut-off 19%)	(Cut-off 30%)	(Cut-off 35%)	(Cut-off 39%)
A Total Correctly Called Observations	76%	85%	89%	90%
B Pre-crisis Periods Correctly Called	71%	70%	70%	70%
C Tranquil Periods Correctly Called	76%	88%	92%	94%
D False Alarms	62%	43%	36%	31%
E Efficiency Measure = B-D	**9%**	**28%**	**34%**	**38%**
Average of above strategies				
A Total Correctly Called Observations	65%	73%	81%	82%
B Pre-crisis Periods Correctly Called	62%	66%	69%	67%
C Tranquil Periods Correctly Called	65%	75%	84%	85%
D False Alarms	50%	42%	37%	34%
E Efficiency Measure = B-D	**12%**	**23%**	**31%**	**32%**

a/ As percentage of the total number of observations. There are two situations in which the observation is correctly called: (i) when the crisis probability exceeds the cut-off point, and a crisis happens in the next 24 months, or (ii) when the crisis probability does not exceed the cut-off point, and no crisis happens in the next 24 months.

b/ As percentage of the total number of actual crisis. A crisis is correctly called when situation (i) of note a/ happens.

c/ As percentage of the total number of tranquil periods. A tranquil period is correctly called when the situation (ii) happens.

d/ As percentage of the total number of alarms. A false alarm occurs when the estimated crisis probability exceeds the cut-off probability (i.e., alarm) but no crisis ensues in the next 24 months.

5. Out-of-Sample Results

5.1. Robustness Tests

To test the performance of the models in fitting the data in the sample may not seem good enough for early warning systems, for which one of the main goals is to provide reasonable out-of-sample performance in crisis detection and prevention. We therefore proceed with out-of-sample tests. In order to do so, we first re-sample the data and discard all observations after December 1998. Then we submit the main specifications of Table 1 to robustness tests in which the EWS, CBS, BBS, and EBS specifications are tested on this new sample.

The result is twofold: on the one hand, a new set of coefficients is provided through the use of the smaller sample; on the other hand, a robustness test checks whether the variables are still significant, and therefore should be maintained in the forecast exercise. The results (Table 5) show that all variables have the expected sign and are statistically significant, except for the banking to total debt ratio (macro debt structure). Goodness-of-fit is still higher for the CBS, BBS, and EBS models (36%, 46%, and 48%, respectively) than for the EWS specification (21%). Also the information criteria are lower in the balance sheet model specifications than in the EWS model, even if the latter has a much shorter model than any of the balance sheet versions.

Table 5: Probit Estimations of External Crisis Probabilities (1991 to 1998) a/ b/

	Sign	EWS		Selected Models					
		Reduced Sample		CBS		BBS		EBS	
		(1)		(2)		(3)		(4)	
Macro Benchmark									
REER	+	0.016	(9.03)	0.021	(8.87)	0.030	(8.49)	0.030	(8.15)
CA/GDP	+	0.007	(3.95)	0.005	(2.68)	0.007	(2.40)	0.010	(3.61)
RGR	+	0.006	(3.59)			0.007	(2.84)	0.009	(3.23)
STD/R	+	0.022	(12.00)	0.019	(9.68)	0.019	(6.95)	0.018	(6.58)
Corporate									
FlevBV	+			0.019	(10.85)	0.007	(2.05)	0.017	(7.40)
STD/WC	+			0.003	(1.77)	0.005	(2.21)	0.006	(2.56)
FlevBV*Bnk	+					0.010	(2.84)		
Financial									
FlevBV	+					0.012	(5.99)	0.012	(5.91)
STD/LTD	+					0.007	(3.48)	0.005	(2.18)
Macro-Balance/Institutional									
CorpD/TotD	-			-0.019	(-8.79)	-0.012	(-5.04)	-0.009	(-3.80)
BankD/TotD	+					-0.001	(-0.38)	-0.001	(-0.55)
CorpD/X	+			0.023	(10.43)				
BkCorpD/X	+					0.020	(8.37)	0.019	(8.04)
Legal									
ShareRight	-							-0.256	(-7.36)
EnforcIndex	-							-0.162	(-3.26)
Constant		-3.450	(-19.78)	-4.602	(-18.89)	-6.962	(-13.77)	-5.559	(-9.95)
Statistics									
Log Likelihood			-643.11		-498.62		-363.54		-345.23
Akaike Criterion			0.80		0.69		0.56		0.53
Schwartz Criterion			0.82		0.72		0.61		0.59
McFadden R-squared			0.21		0.36		0.46		0.48
Crisis Periods (A)			325		325		266		266
Tranquil Periods (B)			1290		1134		1085		1085
Sample Size (A+B)			1615		1459		1351		1351

a/ Heteroskedasticity-consistent QML (Huber/White) z-statistics in brackets.
b/ Type I error probability of 1% corresponds to z-statistics of about 2.57, 5% to 1.96, and 10% to 1
REER (Real effective exchange rate), CA/GDP (Current account over GDP), RGR (Changes in reserves), STD/R (Short-term debt over reserves), Corporate FlevBV (Total Debt/Common Equity (Book Value)), STD/WC (Short-term Debt/Working Capital), FlevBV*Bnk (FlevBV multiplied by Domestic Credit to the Private Sector and Non-financial Public Enterprises as a percentage of GDP), Financial FlevBV (Total Debt/Common Equity (Book Value)), STD/LTD (Short-term Debt/Long-term Debt), CorpD/TotD (Corporate Sector Debt to Foreign Banks/ Total Debt to Foreign Banks), BankD/TotD (Financial Sector Debt to Foreign Banks/ Total Debt to Foreign Banks), CorpD/X (Corporate Sector Debt to Foreign Banks/ Exports), BkCorpD/X (Corporate and Financial Sectors Debt to Foreign Banks/ Exports), ShareRight (Index of shareholders' rights), EnforcIndex (Index of contract enforcement level).

5.2. Out-of-Sample Accuracy of Crisis Probabilities

We checked the accuracy of each model for out-of-sample forecasts using the specifications discussed above (based on the 1991 to 1998 sample period) and the actual data for 1999 through 2001, with the results shown in Table 6 below. There, we can see that, based, as before, on the number of pre-crisis correctly called minus the number of false alarms, out of the balance sheet models, both BBS and EBS specifications are superior to the others at both cut-off values (while CBS is also superior to the others at the higher cut-off). The KLR and EWS specifications are inferior to any balance sheet model, whereas the BP specification is very efficient in the lower cut-off (although still inferior to both BBS and EBS) but does not call any pre-crisis period correctly at the highest cut-off level.

Table 6: Out-of-Sample Accuracy of Crisis Probabilities for the Next 24 Months for Various EWS Specifications a/

		KLR c/	BP d/	EWS Reduced Sample	CBS	BBS	EBS
Cut-off Probability of 50%							
A	Total Correctly Called Observations b/	74%	78%	95%	94%	94%	94%
B	Pre-crisis Periods Correctly Called b/	4%	0%	39%	84%	61%	94%
C	Tranquil Periods Correctly Called b/	100%	100%	99%	94%	96%	94%
D	False Alarms b/	17%	No alarms	29%	51%	50%	50%
E	Efficiency Measure = B-D	**-13%**	**NA**	**9%**	**33%**	**11%**	**44%**
Cut-off Probability of 25%							
A	Total Correctly Called Observations	69%	79%	87%	82%	88%	89%
B	Pre-crisis Periods Correctly Called	25%	80%	74%	94%	100%	100%
C	Tranquil Periods Correctly Called	85%	79%	88%	81%	87%	89%
D	False Alarms	63%	49%	72%	76%	67%	64%
E	Efficiency Measure = B-D	**-38%**	**31%**	**2%**	**18%**	**33%**	**36%**

a/ Our out-of-sample period spans from 1999 to 2001. KLR and BP out-of-sample results span 1995 through 1997.
b/ See footnotes in Table 4.
c/ Kaminsky, Lizondo, and Reinhart original specification as reported in BP (1999, Table 4).
d/ As reported in Berg and Patillo (1999), linear model (Table 4). This model uses reserves over broad money rather than reserves over short-term debt used in the benchmark model reported in Berg et. al. (1999).

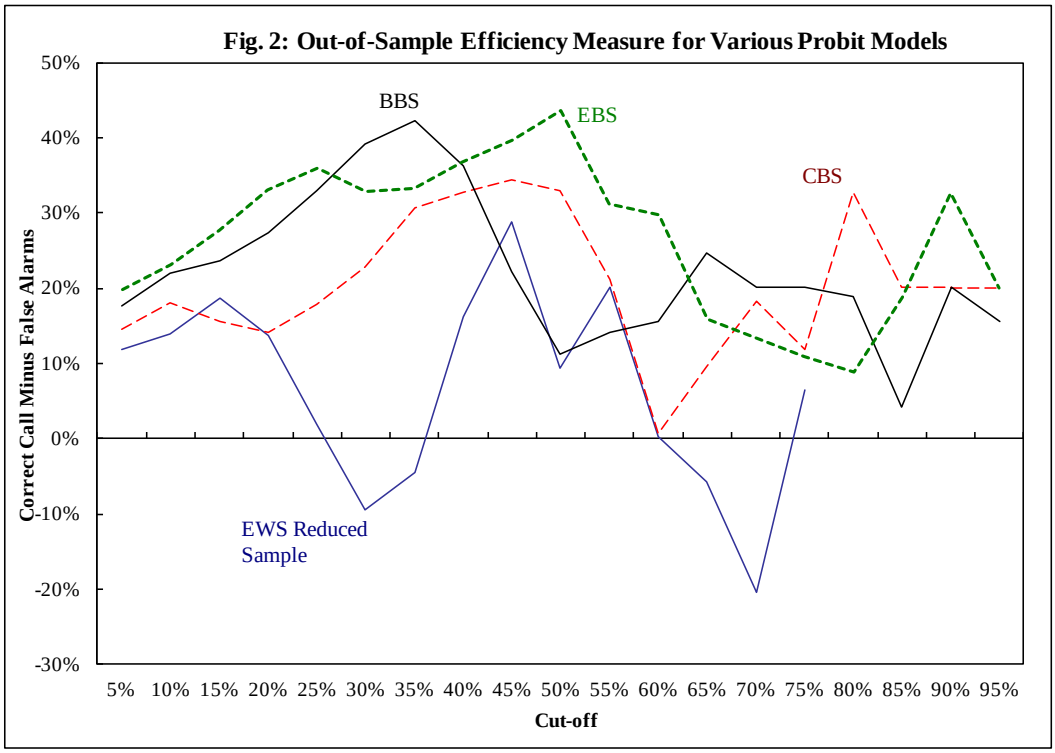
5.3. Calibration Experiment 2: Choice of Cut-off Levels and Risk Tolerance Levels (Out-of-Sample)

Again the question on whether a model is uniformly most powerful at all cut-offs or only at certain values is raised. To answer that, we repeat the experiment described in the in-sample section, and examine the number of pre-crisis correctly called minus the number of false alarms for each model, at each cut-off point.[14]

The results are plotted in Figure 2, where we can see that none of the models are uniformly most powerful, given that there are different preferable models at different cut-off probabilities. In terms of admissibility, however, the EWS is the only one not admissible, given that at each cut-off value the EBS specification is superior to it.[15]

[14] Again due to the lack of data, we could not extend this experiment to the KLR and BP original models.

[15] After the 80% cut-off, the EWS does not provide any alarms.



Finally, we provide the design of optimal strategies to select a cut-off, using the same five criteria we suggested previously for the in-sample analysis: (a) the zero tolerance (or minimum occurrence) of false alarms, (b) the zero tolerance of pre-crisis not called, (c) the highest efficiency measure (pre-crisis called minus false alarms), (d) the threshold of at most 30% of false alarms, and (e) the threshold of at least 70% of pre-crisis correctly called. The detailed results are shown in Table 7. There we can see that all models are admissible, and the choice of the right specification will depend on the goal of the policymaker. Nevertheless, only for strategy 4 is the EWS model performing better, while for all other strategies both BBS and EBS are superior, according to the criterion explained in line E.

6. Conclusion

The latest major wave of emerging market crises was prompted by weaknesses beyond those related to traditional macroeconomic fundamentals. In particular, corporate and financial balance sheets played a prominent role in the causing and transmitting financial turmoil. That feature motivated researchers to develop the so-called third-generation models of currency crises. These models point to the involvement of the private sector and to balance sheet vulnerabilities as core causes of these episodes. Despite the theoretical advances in this strand of research, the empirical studies about EWS often cited in the literature have not incorporated firm-level information either from the corporate or the financial sectors, on the assessment of external vulnerability. In this paper we have aimed to fill this gap by studying the contribution of banks' balance sheets to the EWS of currency crises in emerging market economies. We find that bank's balance sheets improve substantially the predictive power of EWS.

Table 7: Out-of-Sample Performance - Calibration of Cut-off Levels and Design of Optimal Strategy

	EWS Reduced Sample	CBS	BBS	EBS
Strategy 1: Minimum Occurrence of False Alarms	(Cut-off 74%)	(Cut-off 77%)	(Cut-off 87%)	(Cut-off 89%)
A Total Correctly Called Observations a/	94%	96%	96%	96%
B Pre-crisis Periods Correctly Called b/	6%	45%	35%	45%
C Tranquil Periods Correctly Called c/	100%	100%	100%	100%
D False Alarms d/	0%	13%	15%	13%
E Efficiency Measure = B-D	**6%**	**33%**	**20%**	**33%**
Strategy 2: Zero Tolerance of Crisis Not Called	(Cut-off 18%)	(Cut-off 14%)	(Cut-off 30%)	(Cut-off 26%)
A Total Correctly Called Observations	80%	73%	91%	89%
B Pre-crisis Periods Correctly Called	100%	100%	100%	100%
C Tranquil Periods Correctly Called	78%	72%	90%	89%
D False Alarms	77%	82%	61%	64%
E Efficiency Measure = B-D	**23%**	**18%**	**39%**	**36%**
Strategy 3: Highest B-D	(Cut-off 44%)	(Cut-off 43%)	(Cut-off 37%)	(Cut-off 50%)
A Total Correctly Called Observations	96%	93%	93%	94%
B Pre-crisis Periods Correctly Called	58%	90%	97%	94%
C Tranquil Periods Correctly Called	99%	93%	93%	94%
D False Alarms	28%	54%	52%	50%
E Efficiency Measure = B-D	**30%**	**36%**	**44%**	**44%**
Strategy 4: At most 30% of False Alarms	(Cut-off 44%)	(Cut-off 76%)	(Cut-off 79%)	(Cut-off 82%)
A Total Correctly Called Observations	96%	96%	96%	96%
B Pre-crisis Periods Correctly Called	58%	45%	48%	45%
C Tranquil Periods Correctly Called	99%	99%	99%	99%
D False Alarms	28%	26%	25%	26%
E Efficiency Measure = B-D	**30%**	**19%**	**23%**	**19%**
Strategy 5: At Least 70% of Crisis Called	(Cut-off 26%)	(Cut-off 58%)	(Cut-off 45%)	(Cut-off 63%)
A Total Correctly Called Observations	87%	94%	94%	94%
B Pre-crisis Periods Correctly Called	71%	71%	71%	74%
C Tranquil Periods Correctly Called	88%	96%	96%	95%
D False Alarms	73%	48%	49%	50%
E Efficiency Measure = B-D	**-2%**	**23%**	**22%**	**24%**
Average of above strategies				
A Total Correctly Called Observations	91%	91%	94%	94%
B Pre-crisis Periods Correctly Called	59%	70%	70%	72%
C Tranquil Periods Correctly Called	93%	92%	95%	95%
D False Alarms	41%	44%	40%	41%
E Efficiency Measure = B-D	**18%**	**26%**	**30%**	**31%**

a/ As percentage of the total number of observations. There are two situations in which the observation is correctly called: (i) when the crisis probability exceeds the cut-off point, and a crisis happens in the next 24 months, or (ii) when the crisis probability does not exceed the cut-off point, and no crisis happens in the next 24 months.

b/ As percentage of the total number of actual crisis. A crisis is correctly called when situation (i) of note a/ happens.

c/ As percentage of the total number of tranquil periods. A tranquil period is correctly called when the situation (ii) of note a/ happens.

d/ As percentage of the total number of alarms. A false alarm occurs when the estimated crisis probability exceeds the cut-off probability (i.e., alarm) but no crisis ensues in the next 24 months.

Building on the traditional EWS models in the literature, we suggest a class of models that incorporate information on four additional sets of leading indicators of external vulnerability: the corporate sector, the financial sector, the macroeconomic and the legal environments. Using firm-level data, we construct indicators of debt structure, leverage, liquidity, and profitability for the corporate and financial sectors. We also provide balance sheet measures at a macroeconomic level, to capture the business environment that companies and banks are faced with. In addition, we test for the relevance of legal and corporate governance indicators of the private sector protection and regulation in each country. We also control for the propagation of shocks from the corporate sector through the banking sector.

The balance sheet effects are captured in three different models, each of them corresponding to a gradual step toward the parsimonious and selective inclusion of new indicators. We suggest three models that include the corporate and macro balance sheet indicators, financial balance sheet indicators, and legal (corporate governance) indices. The results show that measures of firms' debt structure (corporate short-term debt over working capital, banking short-term debt over long-term debt), firms' leverage (total debt over book value of common equity), macro debt structure (corporate debt to total debt, banking debt to total debt), and macro liquidity (corporate and banking debt to exports) are powerful balance sheet indicators of external vulnerability. Besides those, the index of shareholder's rights was also found to be very significant.

The in-sample results show that this class of models provides superior performance than prominent EWS. For instance, in-sample crisis probabilities right before the Asian crisis show that there is a higher correlation between the results provided by the balance sheet models and

actual results than any other tested specification. Out-of-sample results also support the use of the balance sheet variables. Robustness tests indicate the models are stable for different time-periods, and calibration exercises show that the balance sheet models present superior performance along various possible cut-off probability values.

The results presented here support the third-generation models of currency crises, in which balance sheet information are of extreme relevance to assess external vulnerability of emerging market economies. In particular, we show empirically that these factors were critical during the latest major wave of emerging market crises.

In this paper we also provide calibration experiments that analyze the performance of alternative specifications in a comprehensive range of cut-off probabilities of crisis. Such experiments may assist policymakers on the design of surveillance strategies tailored for different levels of risk tolerance and country specificities.

Risk-based surveillance is a field of increasing prominence in the economic literature, and controlling for balance sheet vulnerabilities has become a central theme in this line of research. Attempts to improve surveillance standards have started to bear fruits as some emerging markets performed relatively better in the 2000s (e.g. Haim and Levy, 2010) and during the financial turmoil of 2008-09 than in previous crisis episodes. The field has gained momentum after the global financial crisis, with the balance sheet approach becoming even more relevant for the surveillance of both emerging and advanced economies (e.g. IMF, 2010). We hope the present study contributes to this field.

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Appendix

Table A1: Financial Sector Variables (FS_i group)

Variable	Expected Sign	Source	Description
			Debt Structure
STD/LTD	+	Worldscope	Short-term Debt/Long-term Debt
			Financial Leverage
EATF	+	Worldscope	Earning Assets/Total Available Funds
FlevMV	+	Worldscope	Total Debt/Common Equity (Market Value)
FlevBV	+	Worldscope	Total Debt/Common Equity (Book Value)
IALI	+	Worldscope	Invested Assets/Total Liabilities
InvLoan/Dep	+	Worldscope	Invested Assets and Loans/Total Deposits
TDTA	+	Worldscope	Total Debt/Total Assets
			Liquidity
ETD	-	Worldscope	Common Equity (Book Value)/Total Deposits
ETK	-	Worldscope	Common Equity (Book Value)/Total Capital
FEITI	-	Worldscope	Foreign Exchange Income/Net Income Before Preferred Dividends
TLTD	-	Worldscope	Total Loans/Total Deposits
			Profitability
EATA	-	Worldscope	Earning Assets/Total Assets
IIEA	-	Worldscope	Net Interest Income/Earning Assets
Margin	-	Worldscope	Net Income before Preferred Dividends / Net Sales or Revenues
RETK	-	Worldscope	Return on Capital (Net Income Before Preferred Dividends + (Interest Expense on Debt - Interest Capitalized)*(1-Tax Rate))/(Last Year's Total Capital + Last Year's Short-term Debt)
ROA	-	Worldscope	Return on Assets (Net Income Before Preferred Dividends + (Interest Expense on Debt - Interest Capitalized)*(1-Tax Rate))/(Last Year's Total Assets)