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CAN CREDIT DEFAULT SWAPS PREDICT FINANCIAL CRISES? EMPIRICAL STUDY ON EMERGING MARKETS

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Abstract:

We explore the informational value of credit default swaps and the extent to which they may be linked to financial crises. After developing a theoretical framework to model the relationship between credit default swap market and equity and currency markets, we apply an empirical study which uses logistic regressions and a panel data sample of emerging markets to assess the ability of these financial instruments to predict crises. Regarding them as reflections of future expectations of investors on the outcomes of currency and equity markets, we find credit default swaps to be a significant indicator explaining the periods proceeding financial crises, at least in equity markets. The inclusion of credit default swaps as a factor in models that predict crises and their ability to improve predictions in equity market is a major contribution of this study to the existing literature.

Keywords: credit default swaps, stock market crises, currency crises, emerging market debt

JEL Classification: F3

1. Introduction

Credit default swaps have been all around the news on the current financial crisis. Economists, investors, politicians and almost everyone seemed to agree that these financial instruments contain important information that can be used to gauge the financial situation during the current financial crisis. An article in Wall Street Journal on Oct 31, 2008 reports:

Investors raise their bets on defaults in EU Countries implying that euro-zone economy heads into recession as costly bank-bailout plans could drive some European governments to default on their debt. Soaring (credit default) swap prices have preceded real calamity. Investor fears about the health of Wall Street firms like Bear Stern Cos. And Lehman Brothers Holding Inc. appeared in swap prices early on and contributed to capital flights that left the firms seeking government help. Credit default swaps have proven themselves a reliable indicator of trouble ahead.

However, can we say that an increase in credit default swap prices implies trouble in the near future for the reference entity? This question prompted us to explore the informational value of credit default swaps and the extent to which they may be linked to financial crises. Specifically, we investigate the ability of fluctuations in these premiums to predict the occurrence of financial crises.

The analysis explores the ability of credit default swaps to predict stock market and currency market crises. The hypothesis is that CDS premiums reflect future expectations of investors on outcomes in currency and equity markets. The premium allows for a clear view of investor perception of risk. Logistic models with panel data from emerging markets are used to assess the crises predictive power of premiums written on sovereign obligations of emerging markets. We check the effect on both stock and currency markets.

To our knowledge, this is the first paper to use credit default swap premiums in predicting financial crises. However, other factors which were created to reflect investor sentiment have been previously used. In principle financial crises should be preceded by periods of increased risk aversion among investors. Curdert and Gex (2007) test whether some main risk aversion indexes are able to predict crises. They find that “risk appetite” tends to decrease prior to financial crises. Also, they do not fail to mention that the opposite case is possible. Crises may follow after periods of strong “risk appetite” during which investors are excessively optimistic and hence create “speculative bubbles” on the prices of risky assets. The recent mortgage crisis is an example of increased investor “risk appetite” prior to crises. According to their findings, risk aversion indicators had more predictive ability in stock market crises then currency crises.

The study is organized as follows. Section 2 briefly discusses the market for credit default swaps and establishes a theoretical basis for relationship between CDS premiums, equity prices and currency trends. Section 3 summarizes the literature on financial crises prediction. Section 4 presents the model specification and the definition of crises. Section 5 describes the panel data. Section 6 presents the results and Section 7 offers concluding remarks.

2.Theoritical Framework

The credit default swap (CDS) market is the largest market of credit derivatives. In a CDS transaction, the protection buyer pays a series of fixed periodic payments (CDS premium) to the protection seller in exchange for a contingent payment in case of a credit event, such as bankruptcy, credit downgrade or a failure to make the scheduled payments. Duffie (1999) explains that the CDS premium is equivalent to swapping the payments from a risky security for the payments of a risk-free security in exchange of a contingent payment in case the risky security defaults. Hence, the premium reflects the credit risk of the underlying asset and is normally quoted in basis points over a reference rate, supposed to be a risk-free rate.

CDSs are actively traded on corporate bonds and sovereign debt. This paper focuses on emerging markets where most contracts reference sovereign obligations. Sovereign CDSs are considered to be the most liquid credit derivative instruments in emerging markets. The usual contract is written on notional amounts of $10 million with a five-year maturity. For instance, a 5 year CDS rate of 200 for a Bulgarian international bond means that it costs $200 per annum to insure a $10,000 face value Bulgarian international bond.

Players in the emerging market CDSs use the contracts for a number of reasons. CDSs allow speculation on the future creditworthiness of countries. Also, they allow exploitation of arbitrage opportunities that may arise from the spread between CDS and the referenced bond. In addition, CDSs are used to manage the exposure to sovereign bonds. Participants in the market utilizing these opportunities range from hedge funds, mutual funds, banks to pension funds. Because of the players involved and the theory that follows, we assume that CDS premium reflects future expectations of the investors and the premium can be used to predict outcomes in currency and equity markets in emerging countries.

First, we discuss our theoretical basis for the effect of the changes in CDS premium on the probability of a currency crisis in the emerging markets. Let N be the notional amount of a contract, **s** be the CDS rate (premium) and p be the default probability of bond payments. Seeker of protection against default will buy the contract if the present value of premium payments will be equal or less than the present value of the expected loss from default:

$$\frac{Ns(1-p)}{1+r} \leq \frac{Np(1-R)}{1+r} \tag{1}$$

where R is the recovery rate in case of default and r is the interest rate. The above equation produces an expected default probability, set by investors, that is proportional to the premium paid:

$$p \leq \frac{s}{s+1-R} \tag{2}$$

where $1 - R$ falls into [0,1]. According to Eq. (2), an increase in the CDS premium (s) at a fixed R, indicates an increased default probability on bond payments of the reference entity (p).

In cases where the reference entity is sovereign debt, the increased default concern translates into a tendency of the currency to depreciate, as concluded by Cochrane (2004). The argument comes from fiscal theory and the theory of optimal distorting taxation. Chochrane uses the analogy of money as a stock in fiscal theory to establish a relation between currency devaluations and fiscal balances. From the theory of optimal distorting taxation, Chochrane argues that a currency crash represents a choice by the government to devalue outstanding nominal debt rather than increase distortionary

taxes. Hence, we expect an increase in the probability of currency crisis in a country when there is an increase in the CDS premium.

Second, the theory for the effect of the changes in CDS premium on the probability of a stock market crisis is based on Merton's (1974) model and its extension to sovereign debt by Chan-Lau & Kim (2004). First, Duffie (1999) notes that the yield from a holding a risky bond and paying a CDS premium, is equivalent to the yield from holding a risk-free bond. However, Chan-Lau & Kim (2004) observe that in practice the risk-free yield and the yield of a risky asset with CDS is not the same, because there is always a difference in bond spreads and CDS spreads evident in CDS-bond differential. The CDS-bond differential partly exists because of the different liquidity in the markets and the cheapest-to-deliver option premium in bonds. However, in the long-run, there should be a co-integration between bond spreads and CDS spreads.

Merton's model links bond and equity prices by taking a balance sheet approach. It argues that if the value of a firm's assets falls below the face value of its debt, the firm defaults. Also, there is a positive correlation between bond and equity prices, and hence equity prices and bond spreads move in opposite direction. Chan-Lau and Kim (2004) extend the model to include sovereign obligations as equivalents of the firms' debt.

From the CDS-bond differential and the relationship between equity prices and bond spreads, we infer that CDS spreads and equity prices move in opposite directions. Furthermore, we use CDS as a source of information for investor expectations in country's equity market, from our assumption that CDSs reflect future market expectations. So, we expect a positive relationship between changes in CDS premium and the probability of a crisis in stock markets.

3.Literature review

The idea underlying the empirical research of crises prediction is to identify some factors that show specific patters prior to periods of crises. The goal is to build a system that assesses the probability of crises at a specific time horizon, taking into consideration all information available at the time of prediction. There are three methodological approaches used in literature on currency and stock market crises. The first approach does not concentrate on the factors that caused the crisis but rather wants to analyze the effects of crisis on some specific sector of the economy. An example is Sachs, Tornell and Velasco (1996), who examine the implications of 1995 crises and try to answer the question of why some emerging markets were hit by the crises while others not.

Kaminsky and Reinhart (1996) devise a methodology called a "signal approach" to identify the periods where a crisis will occur. Numerous papers follow this method which looks for any pattern in individual variables prior to crisis. When a pattern is found (e.g. a deviation from mean up to a certain threshold) a signal is issued by the variable tested. The threshold is chosen so as to minimize the false signals. The advantage of this approach is that it produces easily understandable results for policy purposes. However, it ignores the interaction between independent variables and standard statistical tests cannot be applied.

This paper follows the third approach which eliminates some of the disadvantages of the signal approach by using a limited dependent variable. The method uses a logistic function to evaluate the overall effect of the explanatory variables and predict an outcome, i.e. the probability of the crises, constrained by zero and one. Kumar et al (2003) use a logistic model to study currency crises in 32 developing countries for a period of 15 years.

Factors suggested by Kaminsky, Lizondo and Reinhart (1998) and used in this paper to predict currency crises are: terms of trade, real interest rate, current account deficit, unemployment rate, GDP growth, changes in consumer prices, and returns in stock market indices. For the stock market, factors used in this paper and suggested by Boucher (2004) and also used by Curdert and Gex(2007) are price earnings ratio, stock returns and real interest rates.

The theory of financial crises suggests that economic fundamentals are the main cause of the financial crises. By economic fundamentals, we mean macroeconomic factors such as GDP growth, unemployment, inflation etc. The exact timing of the crises was first linearly determined and the crises had been predictable with economic fundamentals. Kaminsky and Lizondo (1996) specify models that predicted crises by using economic fundamentals in a non-linear fashion. However, economic fundamentals were not the only leading indicators of the crises. Investor behavior and other

political and geographic factors were also taken into consideration. This paper argues for the inclusion of CDS premiums alongside economic fundamental factors to improve the predictability of the crises.

4. Definition of Crises and Model Specification

To test whether sovereign credit default swaps are a leading indicator of financial crises, we construct three models in stock markets and currency markets respectively. The first model is referred to as the "base" model and includes variables usually used in the literature to predict crises. The second model adds to the base model changes in CDS premiums, and will be indicative of the ability of the sovereign CDS to improve the forecasts of the existing models. It does so by checking the significance of the factor in presence of other factors currently used. The third model has changes in CDS premiums as the only independent variable. The dependent variable used is a qualitative variable while the independent variables are exogenous quantitative variables. Therefore, non-linear models are used to link the crisis prediction indicators as the dependent variables to the changes in CDS premiums and other quantitative variables as the independent variables.

Periods of crises are identified by constructing an indicator ($Crisis_{i,t}$), which is used as the dependent variable in the model. The indicator takes the value of 1 if there was a crisis within past 6 months and a value of 0 otherwise. In the regression models that follow, we estimate the probability that the crisis indicator is equal to 1 in a six-month horizon in both currency market and stock market of the emerging countries under consideration. Next, we define crises in currency and stock markets and then explain the regression methodology.

4.1. Currency Market Crisis Definition

Following Sachs, Tornell and Velasco 1996, Kaminski, Lizondo and Reinhart (1998) and Corsetti, Pesenti and Roubini (1999), our models specify a currency crisis when there is a simultaneous increase in currency depreciation and foreign exchange reserves losses. As a convention in literature, a currency pressure index is constructed by the following formula:

$$cpindex_{i,t} = \Delta E_{i,t} - \left(\sigma_{E_{i,t}} / \sigma_{R_{i,t}}\right)\Delta R_{i,t} \tag{3}$$

where $\Delta E_{i,t}$ measures the devaluation of the nominal exchange rate in terms of dollars, $\Delta R_{i,t}$ measures the change in the country's foreign reserves, and $\left(\sigma_{E_{i,t}} / \sigma_{R_{i,t}}\right)$ is the ratio of standard deviations. The index has an advantage of being able to analyze speculative attacks on currencies under both fixed and flexible exchange rate systems. An increase in the reserves reflects foreign currency inflows and lowers the pressure on depreciation of the local currency because of the negative sign in the equation. So, $cpindex_{i,t}$ measures the depreciation pressure of a currency.

We define a currency crisis when the pressure of a currency goes beyond a certain threshold. In empirical studies, the threshold used falls between one and three standard deviations above the mean of the index. This paper uses the following formula to identify the crisis periods:

$$crisis_{i,t} = \begin{cases} 1, & \text{if } cpindex_{i,t} \geq \mu_{cpindex_{i,t}} + 2.0\sigma_{cpindex_{i,t}} \\ 0, & otherwise \end{cases} \tag{4}$$

where $crisis_{i,t}$ is the crisis indicator of country i at time t, $\mu_{cpindex_{i,t}}$ is the sample mean of the pressure index and $\sigma_{cpindex_{i,t}}$ is the standard deviation of the pressure index. With a threshold of two standard deviations above the mean, a total number of 24 crises are identified. Table 1 below shows frequencies of crises and tranquil periods in the respective countries.

Table 1. Number of observations, frequency of crises and tranquil periods in both stock markets and currency markets categorized by country

		Currency Market			Stock Market		
Country	Obs.	Crises	Tranquil	% Crises	Crises	Tranquil	% Crises
Argentina	39	3	36	8.33%	0	39	0.00%
Brazil	83	0	83	0.00%	2	81	2.47%
Bulgaria	95	0	95	0.00%	8	87	9.20%
Chile	68	0	68	0.00%	0	68	0.00%
China	68	3	65	4.62%	6	62	9.68%
Colombia	68	2	66	3.03%	0	68	0.00%
Croatia	95	1	94	1.06%	2	93	2.15%
Hungary	78	0	78	0.00%	0	78	0.00%
India	43	0	43	0.00%	1	42	2.38%
Indonesia	43	1	42	2.38%	0	43	0.00%
Israel	49	0	49	0.00%	0	49	0.00%
Malaysia	82	2	80	2.50%	0	82	0.00%
Mexico	83	2	81	2.47%	0	83	0.00%
Peru	59	1	58	1.72%	2	57	3.51%
Philippines	77	1	76	1.32%	2	75	2.67%
Poland	95	3	92	3.26%	4	91	4.40%
Russia	95	2	93	2.15%	1	94	1.06%
South Africa	95	3	92	3.26%	0	95	0.00%
South Korea	95	0	95	0.00%	1	94	1.06%
Thailand	77	0	77	0.00%	0	77	0.00%
Turkey	77	0	77	0.00%	9	68	13.24%
Total	1564	24	1540	1.56%	38	1526	2.49%

4.2. Stock Market Crisis Definition

To identify the crises periods in stock markets, we follow Mishkin and White (2002) definition of stock market crisis as falls in price of an index below some threshold during a specified period of time. We take the threshold to be 25 percent and the period to be 6 months. Country's main stock market indexes have been used as indicators of the stock market situation. Table 2 in Appendix shows the stock market indices used for respective countries. We use the following formula to identify crises in the emerging stock markets:

$$crisis_{i,t} = \begin{cases} 1, & \text{if } \left(P_{i,t} / P_{i.t-6}\right) - 1 <= -0.25 \\ 0, & otherwise \end{cases} \tag{5}$$

where $crisis_{i,t}$ is the stock market crisis indicator of an emerging country denoted by i at time t, $P_{i,t}$ is the price of the index at time t while $P_{i.t-6}$ is the price of the index six months ago. The formula considers a crisis to be a drop in the index of more than a quarter of its value six month ago. Using the above definition, we identify a total number of 38 crises in our sample data. Table 1 above shows frequencies of crises and tranquil periods in respective countries.

4.3. Model Specification

Three models are tested to see whether changes in sovereign credit default swaps improve forecasts in emerging stock markets and currency crises respectively. The base model includes variables usually used in literature of predicting crises in emerging markets. The second model adds changes in sovereign CDS premiums to the base model, while the third tests the significance of a model which includes only changes in CDS premiums as explanatory variable. Variables in all three models are lagged by one month to check the predictability a crisis a month in advance. In all the regression models for both markets, we use a logistic function of the type:

$$f(x) = \frac{1}{1+e^{-x}} = \frac{e^{x}}{1+e^{x}} . \tag{6}$$

The first model uses the following logistic regression model to estimate the probability of a crisis in stock and currency markets of emerging countries within a one-month horizon by regressing the indicator on variables commonly used in literature:

$$\Pr(crisis_{i,t} = 1) = f\left(\alpha + \sum_{k=1}^{n} \beta_k X_{i,t-1}^{k}\right) \tag{7}$$

where α and β are the coefficients while $X_{i,t-1}^{k}$ are the variables used in past studies on the field. For currency crises model, the variables used are: real interest rate, terms of trade, current account, unemployment rate, GDP growth, inflation and one month stock returns. However, there is not as much literature that addresses stock market crises as there is for currency crises. We use the same factors as in Curdert and Gex (2007) for stock market crises model, namely: price earnings ratio of the indices, one month stock returns and real interest rates.

The second model extends the first model by adding changes in sovereign CDS premiums as a factor predicting crises in emerging markets. The following equation is estimated:

$$\Pr(crisis_{i,t} = 1) = f(\alpha + \sum_{k=1}^{n} \beta_k X_{i,t-1}^{k} + \beta_{n+1} \Delta CDS_{i,t-1}) \tag{8}$$

where $\Delta CDS_{i,t-1} = (CDS_{i,t-1} / CDS_{i,t-2}) - 1$ is the lagged one-month change in sovereign CDS premiums on the international bonds of the emerging countries considered in this paper. Here, fluctuations in CDS are regressed on the presence of other factors used in the first model in order to check its ability to improve the forecasts.

The third model uses the following logistic regression equation to estimate crises probabilities by using changes in sovereign CDS premiums as the only factor:

$$\Pr(crisis_{i,t} = 1) = f(\alpha + \beta \Delta CDS_{i,t-1}) \tag{9}$$

where $\Delta CDS_{i,t-1} = (CDS_{i,t-1} / CDS_{i,t-2}) - 1$ is the lagged one-month change in sovereign CDS premiums as in the second model.

5. Data

The dataset consists of 21 emerging market countries: Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Hungary, India, Indonesia, Israel, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, South Korea, Thailand and Turkey. We use panel data with monthly frequencies starting from the date when CDS quotes were available for the respective reference country until August 2008. We used Bloomberg terminal to retrieve stock market index levels, P/E ratios of indexes and 5 year sovereign credit default swap premiums whereas IMF's International Financial Statistics database was used to retrieve other variables.

The choice of independent variables in both markets was based on earlier studies, and the variables were earlier found to be related to currency and stock market crises respectively. Some variables needed to be created from the retrieved series. In stock markets, six month stock return series were created by using the index price series obtained from Bloomberg. In currency markets, following Kaminsky et al (1998), we created terms of trade as the ratio between exports and imports. Table 2 below summarizes the independent variables and their sources.

Table 2. Data sources and frequencies as they were retrieved

Variables for Stock Market Crises Index	Source	Frequency and Period
Country's Main Stock Market Index	Bloomberg	Monthly, 2000:10 - 2008:8
Independent Variables in Stock Market Model	**Source**	**Frequency and Period**
5 YR Credit Default Swaps in USD	Bloomberg	Monthly, 2000:10 - 2008:8
Price/ Earnings Ratio of Index	Bloomberg	Monthly, 2000:10 - 2008:8
Stock Returns	Bloomberg	Monthly, 2000:10 - 2008:8
Real Interest Rates	IMF IFS line 60 and 64.X	Monthly, 2000:10 - 2008:8
Variables for Currency Market Crises Index	**Source**	**Frequency and Period**
Exchange Rate National Currency per USD	IMF IFS line AE	Monthly, 2000:10 - 2008:8
Total Reserves Minus Gold	IMF IFS line 1L.D	Monthly, 2000:10 - 2008:8
Independent Variables in Currency Market Model	**Source**	**Frequency and Period**
5 YR Credit Default Swaps in USD	Bloomberg	Monthly, 2000:10 - 2008:8
Gross Domestic Product	IMF IFS line 99B	Annual, 2000 - 2008
Current Account	IMF IFS line 78ALD	Annual, 2000 - 2008
Unemployment Rate	IMF IFS line 67R	Annual, 2000 - 2008
Terms of Trade	Kaminsky et al (1998)	Quarterly, 2000:9 - 2008:6
Country's Main Stock Market Returns	Bloomberg	Monthly, 2000:10 - 2008:8
Real Interest Rates	IMF IFS line 60 and 64.X	Monthly, 2000:10 - 2008:8
Change in Consumer Prices	IMF IFS line 64.X	Monthly, 2000:10 - 2008:8

We used linear interpolation to convert the annually and quarterly data observations into monthly frequencies. The variables converted were: GDP growth, current account and unemployment rate. However, in cases where data with lower frequency was available for some countries on these series, we retrieved the lower frequency data. For the monthly series, the last day of the month is used.

By correlation coefficients, we checked whether CDS is showing information that is already contained in another variable. Table 3 below shows correlation matrices for both markets. The correlation coefficient that measures the relationship of CDS to other variables falls in the range of -0.063 (GDP growth) and 0.548 (Inflation). Any coefficient significantly different from 1 and -1 shows that we cannot fit a linear relationship between those variables. Therefore, we argue that information contained in CDS is distinct from the one contained in other variables and hence, it can improve results.

Table 3. Correlation matrices of variables used in stock market and currency market models

Stock Market

	Return	CDS	Real Int Rate	P/E Ratio
One Month Return	1			
CDS	-0.01	1		
Real Interest Rate	0.0279	0.3433	1	
Price/ Earnings Ratio	0.0447	0.0825	-0.0821	1

Currency Market

	CDS	Terms	Curr Account	Unemploy.	Inflation	Real Int Rate	GDP Growth	Return
CDS	1							
Terms of Trade	0.0442	1						
Current Account	-0.0487	0.0426	1					
Unemployment Rate	0.1371	0.3065	-0.1246	1				
Inflation	0.548	0.1443	0.0569	-0.0367	1			
Real Interest Rate	0.1129	0.0884	-0.1359	0.0699	-0.0454	1		
GDP Growth	-0.0639	0.0444	0.1508	-0.1015	0.023	0.0666	1	
One Month Return	0.0049	0.0148	0.1609	-0.0249	0.0377	-0.0614	0.1201	1

Panel data unit root test as suggested by Im *et al.* (2003) is applied to check whether we have stationary variables. The test rejected the null hypothesis that all series are non-stationary against an alternative that all series are stationary at a 10 percent level of significance. Hence, the variables used in the regressions are trend stationary.

6. Empirical Results

Models specified in the methodology were regressed to estimate the variables that affect the probability of stock market crises and currency market crises in emerging markets. We used panel data with one month lagged independent variables. Because of the short time period of the data we possessed, we did only in-sample predictions. Table 4 below shows the coefficients and marginal effects or slope coefficients of the factors supposed to affect the probability of the stock market crises whereas Table 5 below presents the same regression results for the factors assumed to affect the probability of the currency crises. First, we discuss the results in both markets. Then, we explore the predictive ability of our models and finally, we compare the predictive power of models in stock and currency markets.

In the stock market models, all three models proved to be significant. In the first model, the regression on the currently used factors in literature produced a pseudo squared-R of 0.059 and the model proved significant at a one percent confidence level. Unexpectedly, P/E ratios and real interest rates are insignificant in predicting stock market crises. In the second model, we improve the pseudo squared-R to 0.077 after adding the one month changes in the CDS premiums in the base model. One month changes in CDS premiums are statistically significant at one percent and improve forecasts of stock market crashes a month in advance in emerging markets. The factor has the expected positive sign, which reflects the assumption that ceteris paribus, an increase in premiums signals a higher probability of default in emerging stock markets. Also, changes in CDS premiums are significant also in the third model, when they are the only factor predicting crises. So, an increase in the default probability of bond payments by a country, which is derived from the credit default swap premium, can be interpreted as a factor signaling an increase in the probability of a stock market crisis in the same country.

Table 4. Logit regression models predicting stock market crises[1]

Dependent variable: Crisis Indicator	Model (1)		Model (2)		Model (3)	
Independent variables (t-1):	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Constant	-3.505637***		-3.950127***		-3.973741***	
	[0.3481558]		[0.2009473]		[0.1925427]	
Sovereign Credit Defalut Swaps			.0008721***	0.00000119***	0.0010651***	.0000233***
			[0.0003182]	[0.00002]	[0.0002776]	[.00001]
P/E Ratio of Stock Markets	-0.0005738	-6.79e-06	-.000612	-0.00000725		
	[0.0121172]	[0.00014]	[0.0121767]	[0.00014]		
Real Interest Rate	-0.170696	-0.0020196	-.0334392	-0.0020251		
	[0.0560089]	[0.00059]	[0.0307316]	[0.0006]		
One Month Stock Returns	-8.266678***	-0.0978076***	-8.640637***	-0.0978626***		
	[3.192179]	[0.04138]	[2.129019]	[0.04142]		
Observations	1521		1521		1543	
Log Likelihood	-163.73714		-160.6004		-169.41479	
Pseudo squared-R	0.0592		0.0773		0.0296	
Chi-square	20.62		26.89		10.34	
P-Value	0.0000		0.0000		0.0013	

[1]Standard errors are in brackets, * significant at 10%, ** significant at 5%, *** significant at 1%, marginal effects give the estimated slope coefficient, coefficients are estimated for the original logistic model

We do not have the same impressive results in currency markets. The regression on the factors currently used in literature produced a pseudo squared-R of 0.14 with GDP growth and inflation failing to be statistically significant as leading indicators of currency crises. Ceteris paribus, increases in stock returns or real interest rates contribute to lower probability of currency crisis while increases in terms of trade, current account or unemployment rate signal a higher probability of currency crises. Changes in CDS premiums are statistically significant at 5 percent confidence level in the third model and they have the expected positive sign, where an increase in the premiums corresponds to a higher probability of currency crises. However, a test on the slope coefficient of changes in CDS premiums in the second model cannot reject the null hypothesis that the coefficient is significantly different from zero. So, changes in CDS premiums are insignificant in presence of currently used factors in literature. Hence, the inclusion of the factor in the base model does not improve forecasts of currency crises in emerging markets.

However, one cannot draw final results from conclusions by looking at the coefficients and marginal effects of the factors only. Statistics on predictive ability of our models should also be considered. To obtain meaningful statistics about predictions from our data-sample, we set a probability threshold above which, it is decided that the model predicts a crisis. Other studies choose a threshold that maximizes the share of correctly classified observations. We follow Peltonen (2006) and use four different probability thresholds. Table 6 and Table 7 show statistics on predictive ability of our models for different probability thresholds.

Table 5. Logit regression models predicting currency market crises[2]

	Model (1)		Model (2)		Model (3)	
Dependent variable: Crisis Indicator Independent variables (t-1):	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Constant	-6.738983***		-6.487072***		-4.23099***	
	[1.077809]		[1.086092]		[0.2203864]	
Sovereign Credit Defalut Swaps			0.8368797	0.0046655	1.63882**	.0236229***
			[1.062977]	[0.00602]	[0.6597416]	[0.00923]
Terms of Trade	0.8058111**	0.0046468 **	0.5876072**	0.0024199**		
	[0.3655891]	[0.00215]	[0.3637605]	[0.00172]		
Current Account	0.0000107***	6.20e-08***	8.91e-06***	3.67e-08***		
	[4.79e-06]	[0.00000]	[5.11e-06]	[0.00000]		
Unemployment Rate	0.0830174**	0.0004787**	0.0954109**	0.0003929**		
	[0.0354746]	[0.0002]	[0.0356845]	[0.00018]		
Change in Consumer Prices	0.0759931	0.0004382	0.1838124	0.000757		
	[0.0569267]	[0.00036]	[0.0814281]	[0.00045]		
Real Interest Rate	-0.01649704 **	-0.0009513**	-0.1489212**	-0.0006133**		
	[0.0788175]	[0.00045]	[0.0946067]	[0.00039]		
GDP Growth	3.375028	0.0194626	3.520752	0.0144992		
	[4.032087]	[0.0232]	[4.609704]	[0.01952]		
One Month Stock Returns	-8.855517*	-0.0510666*	-9.64336*	-0.0397134*		
	[3.613523]	[0.02639]	[3.751803]	[0.02234]		
Observations	1209		1080		1522	
Log Likelihood	-90.690727		-69.647606		-120.9699	
Pseudo squared-R	0.1439		0.1636		0.0197	
Chi-square	30.48		27.25		4.87	
P-Value	0.0000		0.0006		0.0274	

The statistics on the predictive ability of stock market crises show that the second model outperforms the base model by the share of correctly predicted crises at 0.1 and 0.15 probability

[2]Standard errors are in brackets, * significant at 10%, ** significant at 5%, *** significant at 1%, marginal effects give the estimated slope coefficient, coefficients are estimated for the original logistic model

threshold. The second model correctly predicts 27.27% and 33.33% while the base model predicts 21.05% and 16.67% of the crises at 0.1 and 0.15 thresholds respectively. At 0.25 probability threshold, the base model predicts one crisis and makes no false alarm while the second and third models correctly predict two crises out of five. Adding CDS premium changes to the base model improves the predictive ability and at best, it predicts 40% of the crises.

Changes in CDS premiums are statistically insignificant in the second model, and hence the predictive ability of the base model and the second model is the same. However, the CDS premiums are significant in the third model but underperform the base model in the predictive ability. The model does not predict any crises at a probability threshold of more than 0.1. At a threshold of 0.05, the third model correctly predicts only 4.76% of the crises while the base model predicts 16.13%. At best, the base model correctly predicts 42.46% of the crises at 0.1 and 0.15 probability thresholds.

Table 6. Forecasts of crises probabilities in currency market models[3]

Currency Market		Number of crises predicted	Crises Predicted Correctly Pr(D| +)	False Alarms Pr(~D| +)	Sensitivity Pr(+| D)	Specificity Pr(-| ~D)	Share of correctly classified obs.
Model (1) Threshhold							
	0.05	62	16.13%	83.87%	47.62%	95.62%	94.79%
	0.1	7	42.86%	57.14%	14.29%	99.66%	98.18%
	0.15	7	42.86%	57.14%	14.29%	99.66%	98.18%
	0.25	5	40.00%	60.00%	9.52%	99.75%	98.18%
Model (2) Threshhold							
	0.05	62	16.13%	83.87%	47.62%	95.62%	94.79%
	0.1	7	42.86%	57.14%	14.29%	99.66%	98.18%
	0.15	7	42.86%	57.14%	14.29%	99.66%	98.18%
	0.25	5	40.00%	60.00%	9.52%	99.75%	98.18%
Model (3) Threshhold							
	0.05	21	4.76%	95.24%	4.17%	98.66%	97.17%
	0.1	1	0.00%	100.00%	0.00%	99.93%	98.36%
	0.15	0	0.00%	0.00%	0.00%	100.00%	98.42%
	0.25	0	0.00%	0.00%	0.00%	100.00%	98.42%

Table 7. Forecasts of crises probabilities in stock market models*

Stock Market		Number of crises predicted	Crises Predicted Correctly Pr(D| +)	False Alarms Pr(~D| +)	Sensitivity Pr(+| D)	Specificity Pr(-| ~D)	Share of correctly classified obs.
Model (1) Threshhold							
	0.05	112	12.50%	87.50%	37.84%	93.40%	92.04%
	0.1	19	21.05%	78.95%	10.81%	98.99%	96.84%
	0.15	6	16.67%	83.33%	2.70%	99.66%	97.30%
	0.25	1	100.00%	0.00%	2.70%	100.00%	97.63%
Model (2) Threshhold							
	0.05	93	11.83%	88.17%	29.73%	94.47%	92.90%
	0.1	22	27.27%	72.73%	16.22%	98.92%	96.91%
	0.15	9	33.33%	66.67%	8.11%	99.60%	97.37%
	0.25	5	40.00%	60.00%	5.41%	99.80%	97.50%
Model (3) Threshhold							
	0.05	23	8.70%	91.30%	5.41%	98.61%	96.37%
	0.1	8	25.00%	75.00%	5.41%	99.60%	97.34%
	0.15	7	28.57%	71.43%	5.41%	99.67%	97.41%
	0.25	5	40.00%	60.00%	5.41%	99.80%	97.54%

[3]* Crises predicted correctly were classified when there was a prediction that a crisis will happen and the crisis in fact happened. False alarms were considered when a crisis was predicted but it did not take place in reality. Sensitivity measures the percent probability of a crisis to have been predicted when a crisis happens. Specificity measures the probability that no crisis is predicted when no crisis is taking place. Share of correctly classified observations measures the percentage of correctly predicted situations in the market out of all the data points used. D stands for "crises happening" while ~D is the opposite. + stands for "predicted crisis" while – stands for "no crisis predicted".

Looking at country-specific forecasts, the most successful prediction of a stock market crisis was for the Brazilian Bovespa index. Also, the model produced successful predictions for the Turkish stock market with the exception of predicted values for 2003. The worst results from the stock market model are for the Russian stock market index where we have a predicted crisis probability of more than 20 percent and yet there is no crisis as defined in this paper. Figure 1 below shows four graphs of interest for forecasts for stock market crises by country.

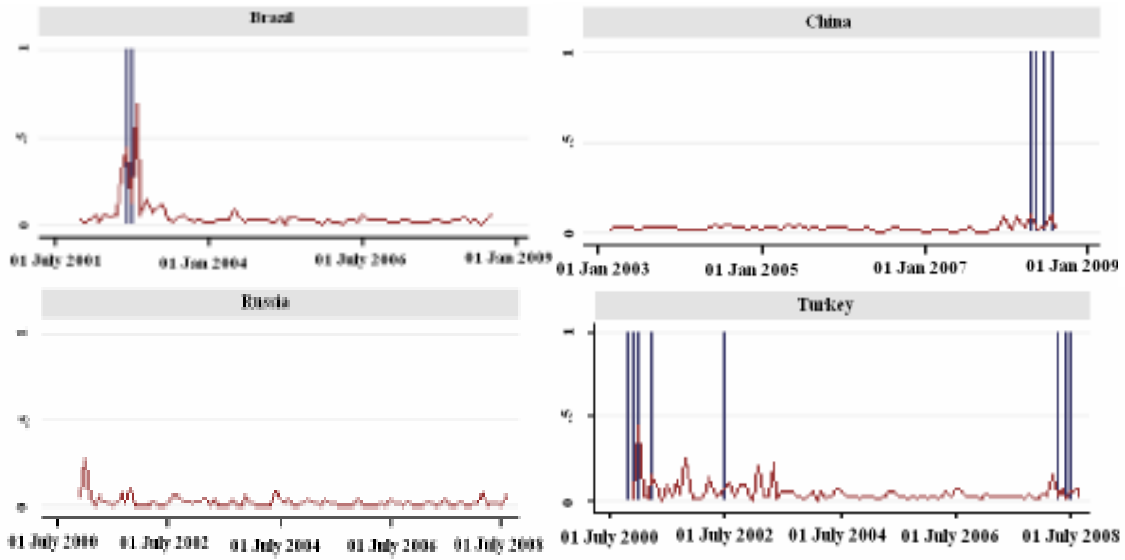

Figure 1. Graphs' of model (2) forecasts for stock market crises for four countries. The blue bar shows the occurrence of a crisis as defined in this paper and the red line shows the estimated probability of a crisis by model(2)

On the other hand, the most successful prediction of a currency market crisis was for the South African Rand in 2003, although we don't have a predicted crisis probability of more than 10 percent for this currency. The worst result from the model that predicts currency crises was for the Chinese Renminbi. The model predicts a currency crash with more than 50 percent probability during the second quarter of 2008 although there is no crisis. Figure 2 below shows the graphs of forecasts for currency market crises by country.

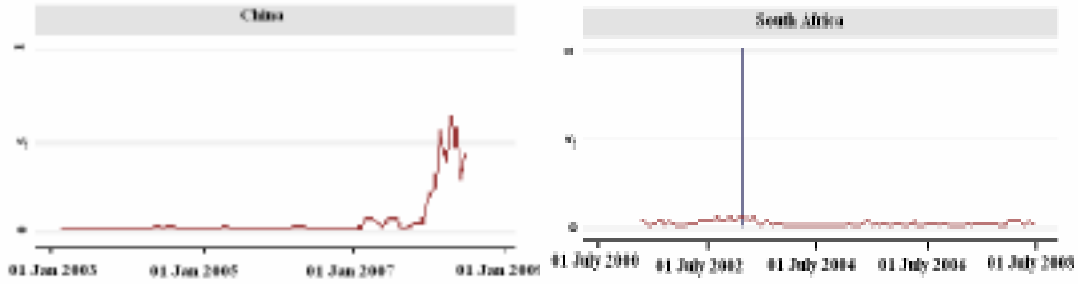

Figure 2. Graphs' of model (2) forecasts for currency market crises for two currencies.
The blue bar shows the occurrence of a crisis as defined in this paper and the red line shows the estimated probability of a crisis by model(2)

To sum up, changes in sovereign credit default swap premiums have statistically significant impact on the probability of stock market crises in emerging markets, while the same is not true for the currency crises. Credit default swaps alone were able to predict 40% of the stock market crises and 4.76% of the currency market crises.

7. Conclusion

The purpose of this study was to examine whether changes in sovereign credit default swap premiums were able to predict stock market or currency market crises in emerging markets. The logistic regression results show that the one month change in a country CDS premium tends to increase one month ahead of a crisis in the stock market, while it does not have a significant implication for the currency market. Also, the predictive power was satisfactory for stock market crises. By contrast, these financial instruments were found to be insignificant in presence of other factors in explaining currency crises. The findings here confirm the results from Cudert and Cox (2007) that factors that measure investor sentiment have more predictive power in stock market crises than in currency crises. The inclusion of such a financial instrument as a factor in models that predict financial crises and its ability to improve predictions in stock market crises is the major contribution of this study in the existing literature. We established that fluctuations in CDS premiums signal trouble in stock markets.

Recently, because of the critiques directed to the industry for the low level of transparency in the CDS market, The Depository Trust & Clearing Corp. has decided to publish quotes of CDS online and free for public. It will be interesting to see whether this move will have an effect on the crises predictive ability of these instruments in the future. This issue is beyond the scope of this study; however, the informational value of these financial instruments is without doubt immense.

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