

Option-Based Risk Aversion Indicators for Predicting Currency Crises in Emerging Markets

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Non-Technical Summary

Relying solely on economic variables to predict currency crises has been considered insufficient by the literature. Thinking in terms of financial variables and as currency crises generally coincide with periods in which risk aversion increases, it is not unusual to find papers that incorporate risk aversion indicators in economic models to predict these crises. However, they usually deal with risk aversion indicators built in a backward-looking way, i.e., estimated from historical time series data.

As option prices can be used to extract information about risk aversion in a forward-looking way, I consider risk-aversion indicators extracted from these prices in traditional currency crises prediction models.

Three risk aversion indicators extracted from foreign exchange options data are employed in currency crises models. Two uncertainty indexes are alternatively considered, given its connection with risk aversion measures.

The goal of this paper is to examine the role of these risk aversion indicators on the probability of currency crises in a 12-month horizon. Fourteen emerging currencies are studied from January 2007 to July 2018, covering the Subprime and the European crises. I use panel data regressions to estimate those probabilities.

The results show option-based risk aversion indicators have the expected positive sign and are significant to predict crises. When added to traditional economic variables, they improve quality and predictive power of those regressions. EPU index, the only one not extracted from options, is the exception, exhibiting an unexpected negative sign.

This paper innovates as it adds risk aversion indicators solely extracted from option prices to the traditional economic models. As an additional contribution to the related literature, the paper incorporates the recent Subprime and European crises and the subsequent crises in emerging markets.

Sumário Não Técnico

Levar em conta exclusivamente variáveis econômicas para prever crises cambiais tem sido considerado insuficiente pela literatura. Pensando em termos de variáveis financeiras e em como crises cambiais geralmente coincidem com períodos em que a aversão ao risco aumenta, não é incomum encontrar trabalhos que incorporem indicadores de aversão ao risco a modelos econômicos para prever essas crises. No entanto, eles geralmente lidam com indicadores de aversão ao risco construídos de uma maneira backward-looking, estimada a partir de dados históricos de séries temporais.

Como os preços das opções podem ser usados para extrair informações sobre a aversão ao risco de uma maneira forward-looking, este artigo considera os indicadores de aversão ao risco extraídos desses preços nos modelos tradicionais de previsão de crises cambiais.

Três indicadores de aversão ao risco extraídos de dados de opções de câmbio são empregados nos modelos de crises cambiais. Dois índices de incerteza são alternativamente considerados, dadas suas relaç ões com medidas de aversão ao risco.

O objetivo deste artigo é examinar o papel desses indicadores de aversão ao risco na probabilidade de crises cambiais num horizonte de 12 meses. Quatorze moedas emergentes são estudadas entre janeiro de 2007 e julho de 2018, cobrindo as crises do Subprime e da Europa. Foram utilizadas regressões de dados em painel para estimar essas probabilidades.

Os resultados mostram que os indicadores de aversão ao risco baseados em opções têm o esperado sinal positivo e são significativos para prever as crises. Quando adicionado a variáveis econômicas tradicionais, melhoram a qualidade e o poder preditivo dessas regressões. O índice EPU, o único não extraído das opções, é a exceção, apresentando um sinal negativo inesperado.

Este artigo inova ao adicionar indicadores de aversão ao risco extraídos apenas dos preços das opções aos modelos econômicos tradicionais. Outra contribuição para a literatura relacionada é que o artigo incorpora as recentes crises do Subprime e da Europa e as crises subsequentes nos mercados emergentes.

Option-Based Risk Aversion Indicators for Predicting Currency Crises in Emerging Markets

Jaqueline Terra Moura Marins*

Abstract

Currency crises generally coincide with periods in which risk aversion increases. Option prices can be used to extract information about risk aversion in a forward-looking way. With this advantage in mind, this paper tests whether some option-based risk aversion indicators can improve currency crises prediction. The sample data refer to 14 emerging currencies from January 2007 to July 2018, covering the Subprime and the European crises. I use a probit model for panel data of these countries to estimate the probability of currency crises in a 12-month horizon. The results show option-based risk aversion indicators have the expected positive sign and are statistically significant to predict those crises. When added to traditional control variables used in the probit model, they generally improve quality and predictive power of the regressions.

Keywords: risk aversion indexes, currency options and financial crises. **JEL Classification**: C35, F31, G13.

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1 Introduction

A common understanding among financial crises studies is economic variables are insufficient to predict them. Zouaoui (2010) reviews several papers which recognize this difficulty of traditional economic models and propose ways of dealing with it. According to these papers, financial markets, namely currency and stock markets, are highly volatile and market prices fluctuation is well above what is predicted by changes in economic indicators.

Some authors deal with this difficulty by making use of leading indicators of financial crises based on risk aversion, since these crises generally coincide with periods in which risk aversion increases. Coudert & Gex (2008), for example, make use of risk aversion indicators commonly used by financial institutions to predict crises, such as GRAI (Global Risk Aversion Index), VIX (Chicago Board of Exchange Volatility Index), LCVI (J.P. Morgan Liquidity, Credit and Volatility Index) and ICI (State Street Investor Confidence Index).

Option prices can also be used to extract information on risk aversion (Jackwerth, 2000; Tarashev et al., 2003; Gai & Vause, 2006; Bollerslev et al., 2011). The advantage here is option markets exhibit high volatility and are forward-looking, so that every new development is readily incorporated into agents' information set. As Li et al. (2015) find, derivative markets are more informative than spot markets, and if a model for predicting financial crises incorporates information revealed from derivative markets, it has potential to provide early signals of these crises. According to the authors, the theoretical reason is the higher financial leverage offered by derivatives, which attracts greater participation by informed traders. Greater leverage implies greater risk, which therefore increases the incentives for information dissemination and price discovery.

I use three risk aversion indicators extracted from options data in currency crisis models: Empirical Risk Premium (ERP), Model-Free Volatility Risk Premium (MFVRP) and At-the-Money Volatility Risk Premium (ATMVRP). I also make use of two uncertainty indexes, given its connection with risk aversion measures. The first one is the Volatility Smile-based Uncertainty Index (VSU), which is also extracted from currency option prices (Vicente & Marins, 2019). The second one is the Economic Policy Uncertainty Index (EPU), which, although not option-based, has become a reference indicator of uncertainty (Baker et al. (2016)). All of them will be denominated risk aversion indicators from now on.

ERP is obtained by comparing the expected values of real-world and risk-neutral probabilities calculated on currency option prices. VSU captures the difference between the Black & Scholes (1973) implied volatilities extracted from currency options and a model-free concept of option volatility. MFVRP measures the difference between realized and model-free risk-neutral volatilities. ATMVRP captures the difference between realized and at-the-money volatilities. EPU is based on the frequency of word roots related to economic policy uncertainty in newspapers.

The goal of this paper is to examine the role of these risk aversion indicators on prediction of currency crises. I follow the methodological approach of Coudert & Gex (2008), i.e., a probit model to evaluate the probability of currency crises using panel data of emerging countries in three versions: a base model of economic indicators as controls; control variables added for each risk aversion indicator; and risk indicators taken alone. The sample period begins in January 2007 and ends in June 2018. This period covers the Subprime crisis in the middle of 2007, the European crisis in the middle of 2010 and the subsequent crises in emerging markets.

The results show the option-based risk aversion indicators have the expected positive sign and are statistically significant in the probit regressions for currency crises. The EPU index, the only one not extracted from options, shows an unexpected negative sign. When ERP is added to traditional control

variables, it improves quality and predictive power of these regressions.

This paper diverges from previous studies because it considers risk aversion indicators solely extracted from option prices. Also, I deal with uncommon versions of these types of risk aversion indicators. ERP, the way it is obtained here, stands apart from its traditional version that uses historical data to estimate real-world probabilities. VSU is a new index. MFVRP used here considers model-free implied volatility instead of the Black & Scholes implied volatility. The role of emerging markets EPU index on predicting currency crises, as far as I know, has never been directly investigated. Besides, I deal with country-specific risk aversion indexes instead of global ones. Some authors wrongly justify the use of global indexes across different countries by arguing investors' risk aversion is the same in all markets and rational investors maximize their expected gains by making investment choices across all types of assets. However, markets are not perfect in terms of capital mobility, especially in emerging economies. Therefore, risk aversion indexes evaluated individually for each country seem to be more appropriate.

Another contribution of this article is to incorporate the recent Subprime and European crises to the literature. Although there is extensive literature related to the Early Warning System to predict currency crises, it is not updated.¹

The remainder of this paper is organized as follows. The second section is devoted to explaining in more detail the aversion indicators and the model used to estimate currency crisis probabilities. The third section presents and interprets the model's results. The fourth section concludes the study.

2 Methodology

In this paper, I consider a panel data of 14 emerging countries followed during nearly 12 years, from January 2007 to June 2018. As currency options data are required to calculate the risk aversion indexes, their availability determined the sample period. I select currency options set to expire in one month at the beginning of each month to obtain monthly data. In spite of intending to predict currency crisis in a 12-month horizon, one-month currency options are preferred over one-year options as they are more liquid.² The emerging markets currencies are the Brazilian Real (BRL), Indian Rupee (INR), Mexican Peso (MXN), Russian Ruble (RUB), Chilean Peso (CLP), Singapore Dollar (SGD), South African Rand (ZAR), Turkish Lira (TRY), Colombian Peso (COP), Malaysian Ringgit (MYR), Indonesian Rupiah (IDR), Israel Shekel (ILS), Philippine Peso (PHP) and Thai Baht (THB).

2.1 Risk aversion indicators

2.2 Empirical Risk Premium

ERP is obtained from currency options prices extracted from Bloomberg. All quotes are in terms of emerging market currency per U.S. Dollar. ERP is evaluated by comparing the risk-neutral probability distribution (RND) of the currency price in dollar terms with its real-world distribution (RWD). More specifically, ERP is defined as the difference between the means of the two distributions, as below:

$$\mu = \frac{1}{T} \ln(\frac{E^P(S_T)}{E^Q(S_T)}),\tag{1}$$

¹Kaminsky et al.(1998), Kumar et al. (2003), Bussiere & Fratzscher (2006), and Coudert & Gex (2008).

²The correlation coefficients between one-month risk aversion indexes and their respective one-year versions are all positive: 18% for Empirical Risk Premium, 48% for VSU, and about 90% for VRP's. Since the correlation between the 1-month and 1-year Empirical Risk Premium was not as high as that of the other indexes, I have made one more assessment: I added this 1-year measure to the respective regression models and found not only is it not significant, but also the 1-month measurement did not change its significance with this inclusion.

where $E^P(S_T)$ is the expectation of the RWD function, $E^Q(S_T)$ is the expectation of the RND and T is the option's maturity.

I compute the RND using the results of Breeden & Litzenberger (1978). They show the risk-neutral probability density of an asset x is the second derivative of the price of a call c on this asset with respect to its exercise price K. This has become a standard technique for extracting information on the future course of asset prices from options contracts. Applying this result to the currency market, I have:

$$f_{t,T}^{Q}(x) = e^{(rT)} \left. \frac{\partial^2 c_t(T,K)}{\partial K^2} \right|_{K=x_T},\tag{2}$$

where $f_{t,T}^Q(x)$ is the risk-neutral probability distribution of the country currency in dollar terms.

RWD can be estimated in essentially two ways. The first one seeks to estimate the utility-function transformations of the RNDs that determine investors' preferences for risk, like in Bliss & Panigirtzoglou (2004). The second way also seeks to transform RND into RWD, but it does not require the function performing the calibration to be a utility function purporting to represent investors' risk preferences, like in Fackler & King (1990), Liu et al. (2007) and Vincent-Humphreys & Noss (2012). I follow this second approach. It is more empirical in that it seeks the function that best fits the RNDs obtained from a given set of observed data, without requiring this function fits an underlying model of agents' behavior. According to these authors, probability densities that reflect rational agents' real-world expectations should, on average, be unbiased predictors of the possible outcomes. If risk-neutral PDFs are biased, the difference between the RND and the estimated RWD of prices as later observed provides an indication of the degree and the nature of risk aversion of the representative agent. To the extent that this difference displays a systematic pattern over time, it may be exploited to adjust the RNDs over as yet unobserved future prices to estimate agents' real-world expectations. The authors use the highly flexible, yet parsimonious, beta distribution function to deliver that calibration of RNDs into RWDs. Although the beta distribution depends on only two parameters, it nests many simple forms of transformation such as a mean shift, mean-preserving changes in variance and changes involving mean, variance and skewness.

The calibration approach that transforms RNDs into RWDs can be represented by the following equations:

$$F_{t,T}^{P}(x) = C(F_{t,T}^{Q}(x)),$$
(3)

where $F_{t,T}^P(x)$ is the option implied risk-neutral cumulative probability function of x at time t for options expiring at T, $F_{t,T}^Q(x)$ is the associated real world cumulative function and C(t) is the calibration function.

$$f_{t,T}^{P}(x) = C'(F_{t,T}^{Q}(x))f_{t,T}^{Q}(x),$$
(4)

where $f_{t,T}^Q(x)$ is the option implied risk-neutral density of x at time t for options expiring at T and $f_{t,T}^P(x)$ is the associated real world density.

If C is a beta distribution, equation (4) becomes:

$$f_{t,T}^{P}(x) = f_{t,T}^{B}(F_{t,T}^{Q}(x)|j,k)f_{t,T}^{Q}(x),$$
(5)

where $f_{t,T}^B(x/j,k)$ is the probability density function of the beta distribution with parameters *j* and *k*.

Estimating the RWDs from the set of historical RNDs and price outturns therefore amounts to estimating the parameters j and k of the beta distribution.

2.3 Model-Free Volatility Risk Premium

MFVRP is the difference between realized and risk-neutral volatilities and is used by market participants as a measure for the market-implied risk aversion. The traditional approach considers the ex-ante riskneutral expectation of the future return volatility from t to $t + \tau$ and the ex-post realized return volatility from $t - \tau$ to t. According to Ornelas (2017), this is a strange concept, since it compares the risk-neutral volatility forecast between t and $t + \tau$ with a backwards realized volatility between $t - \tau$ and t. There is a mismatch between the period for which option traders forecast volatility and the period for which volatility is measured. The market may expect volatility in the future different from the past. This is referred to as the backward approach.

The alternative approach, which I use here, has a forward looking perspective instead, as it compares the risk-neutral volatility forecasted between t and $t + \tau$ with the future realized volatility also between t and $t + \tau$. The forecasted risk-neutral volatility is compared to the realized volatility for the same period. This is called the forward approach.

In this VRP forward approach, I also make use of model-free volatility measures, which, according to Bollerslev et al. (2011), have figured prominently in the recent financial academic literature. Model-free realized volatilities are computed by summing squared returns from high-frequency data over short time intervals during the trading day. Model-free risk-neutral volatilities are computed from option prices without the use of any particular option-pricing model, not relying on the Black & Scholes pricing formula.

Daily realized volatilities are obtained directly from Bloomberg with a frequency of 30 minutes for currency returns. Model-free risk-neutral volatilities are obtained according to Bakshi et al. (2003), already mentioned in the section that describes the VSU index.

MFVRP is then defined by:

$$MFVRP_t = \sigma_{t-\tau,t} - E^Q(\sigma_{t-\tau,t}), \tag{6}$$

where *MFVRP_t* is the Model-Free Volatility Risk Premium at time t, $\sigma_{t-\tau,t}$ is the realized volatility between $t-\tau$ and t and $E^Q(\sigma_{t-T,t})$ is the annualized model-free risk-neutral volatility from time $t-\tau$ until time t. This method uses only information available at time t. Unlike the backward approach, which uses current time t risk-neutral volatility, the forward approach uses risk-neutral volatility with a τ lag, i.e., the risk-neutral volatility is old information.³

2.4 At-the-Money Volatility Risk Premium

Here I calculate the volatility risk premium over at-the-money volatilities instead of using volatilities obtained with the range of all strikes through a model-free approach. As ATM options are the most traded options, their prices and volatilities are more reliable. Besides, as Ornelas (2017) points out, the predictive ability of currency risk-neutral densities are higher in the center than in the tails, which provides evidence of the better informative power of ATM options over other options.

ATMVRP is then the difference between realized and at-the-money volatilities, according to the following equation:

$$ATMVRP_t = \sigma_{t-\tau,t} - E^Q(\sigma_{t-\tau,t}), \tag{7}$$

where $ATMVRP_t$ is the At-the-Money Volatility Risk Premium at time *t*, $\sigma_{t-\tau,t}$ is the realized volatility between $t-\tau$ and t and $E^Q(\sigma_{t-T,t})$ is the annualized At-the-Money volatility from time $t-\tau$ until time *t*.

³Bollerslev et al. (2009) and Ornelas (2017) present these approaches to calculate VRP in detail.

Volatilities of at-the-money currency options are obtained directly from Bloomberg.

2.5 Volatility Smile-based Uncertainty Index

VSU is the uncertainty index proposed in Vicente & Marins (2019). Like ERP, VSU is also obtained from foreign exchange option data, extracted from Bloomberg. The extracted data come in the form of volatility surfaces of currency options.⁴ I use call and put options data with five different delta values: 10, 15, 25, 35 and 50%. I select currency options expiring in one month at the beginning of each month to obtain monthly data.

The proposed uncertainty measure uses two concepts of volatilities extracted from options prices: the Black & Scholes (1973) and the Bakshi et al. (2003) implied volatilities. The first one is obtained by inverting the Black & Scholes formula, so it is considered model-dependent. The second one, proposed by Bakshi, Kapadia and Madan, does not assume a specific probability distribution for the underlying asset, so it is a model-free volatility measure. As Kelly et al. (2016) point out, "when there is no uncertainty, option prices are governed by the Black & Scholes formula, so that implied volatility equals expected volatility..." In the same line of argumentation, the Black & Scholes implied volatility refers to risk and does not consider uncertainty. Therefore, differences between the two implied volatilities should reflect a measure of uncertainty. This is the intuition behind the VSU measure.

$$VSU = \sum_{\Delta_{C,P}} abs(ImpVol_{C,P} - ModelFreeVol),$$
(8)

where $\Delta_{C,P}$ represents the delta values from calls and puts on the volatility surface provided by Bloomberg (10, 15, 25, 35 and 50%), ImpVol_{C,P} are the implied volatilities of these calls and puts and ModelFreeVol_{C,P} are their model-free volatilities.

Economic Policy Uncertainty Index 2.6

EPU index is the most known uncertainty index nowadays. It was developed by Baker et al. (2016) and is based on newspaper coverage frequency. The authors select the most relevant newspapers in a country and perform month-by-month searches of each paper for terms related to economic and policy uncertainty. EPU Index is available for 24 countries, including G10 ones. It also has a global version which is a GDPweighted average of the national EPU indexes. In my sample of countries, I use the global version for Turkey, Malaysia, Indonesia, Israel, Philippines and Thailand. Although EPU index is not option-based, I use it as a risk aversion indicator because of its wide popularity as an uncertainty measure.

Defining currency crises 2.7

I use the usual crisis identification method in the literature, based on the construction of "pressure indicators" (Kaminsky et al., 1998). In the case of currency crises, the pressure indicator is a weighted average of the currency's depreciation of country i in month t, e_t^i , and relative losses in international reserves⁵, $r_{i,t}$, according to:

$$C_{i,t}^{\rm FL} = \alpha_{i,t} e_{i,t} + (1 - \alpha_{i,t}) r_{i,t}$$
(9)

⁴Actually, Bloomberg's original data consist of options strategies in the form of risk reversals, butterflies and at-the-money volatilities. Ornelas (2016) gives an appropriate description of these option data provided by Bloomberg.

⁵In the case of Brazil, I considered the joint exposure of international reserves plus non-deliverable derivatives, as Brazil actively used these instruments during the period. 10

and

$$\alpha_{i,t} = \frac{\frac{1}{var_t(e_{i,t})}}{\frac{1}{var_t(e_{i,t})} + \frac{1}{var_t(r_{i,t})}},$$
(10)

where $\alpha_{i,t}$ is the weighting between the two series, which is inversely proportional to their conditional variance. When the pressure indicator goes above a certain threshold, a currency crisis is identified. The threshold used is generally two or three standard-deviations above the mean. Three standard-deviations seemed too restrictive for my sample. Therefore, I chose two standard-deviations as the currency crisis threshold. The currency crisis indicator $C^{i,t}$ then becomes:

$$C_{i,t}^{Currency} = \begin{cases} 1, & \text{if } C_{i,t}^{\text{FL}} > \overline{C}_{i,t}^{\text{FL}} + 2\sigma_{i,t} \\ 0, & \text{otherwise.} \end{cases}$$

The average and the standard-deviation are moving concepts, firstly calculated from January 1997, 10 years before the beginning of the sample period. As in Coudert & Gex (2008), I do not consider a crisis identified within a 12-month period following another crisis, so it is automatically canceled out. In total, 26 currency crises are detected for the 14 countries (Table 1). It can be seen the starting points of the crises are concentrated around two periods, 2007.2 and 2010.2, capturing the effects of US Subprime and European crises respectively.

Table 1: Identified currency crises

January 2007	Chile and Colombia
April 2007	Philippines
August 2007	India and Singapore
September 2007	Malaysia
October 2007	Brazil, Mexico, Chile, South Africa, Turkey, Indonesia and Israel
January 2008	Russia
September 2010	India, Mexico, Chile, Singapore, South Africa, Malaysia and Indonesia
November 2010	Israel
May 2012	South Africa
December 2013	Russia and Malaysia
November 2015	India

Notes: This table presents the identified currency crises and their beginning month, according to the crisis definition explained previously.

To construct the dependent variable, $I_{i,t}$, I define it as a binary variable that equals one for the 12 months preceding the crisis and the month when the crisis started and 0 in the quiet periods. This way, the probability of a crisis is estimated within a one-year horizon.

$$I_{i,t} = \begin{cases} 1, & \text{if } \exists k \in \{0, \dots, 12\} \text{ such as } C_{i,t+k} = 1\\ 0, & \text{otherwise.} \end{cases}$$

2.8 The Probit Model

Here I use three types of models to estimate crisis probability in a one-year horizon, as in Coudert & Gex (2008). All of them make use of a probit specification. The base model (Model 1) only contains the control variables usually employed to predict currency crises.

$$Pr(I_{i,t} = 1) = f(\alpha_0 + \sum_{k=1}^n \alpha_k X_{i,t}^k),$$
(11)

where I_t^i is the crisis indicator described above, $X_{i,t}^k$ are the *k* controls for crises and *f* is the standard normal probability density function.

Model 2 adds one of the five risk aversion indicators presented above, $\lambda_{i,t}$, among the explanatory variables. Its specification is:

$$Pr(I_{i,t} = 1) = f(\alpha_0 + \sum_{k=1}^n \alpha_k X_{i,t}^k + \alpha_{n+1} \lambda_{i,t}).$$
(12)

Model 3 only uses risk aversion indicators as dependent variables:

$$Pr(I_{i,t}=1) = f(\alpha_0 + \alpha_{n+1}\lambda_{i,t}).$$
(13)

The control variables I use for currency crises are those commonly found in the literature: real exchange rate (country currency against the US Dollar), official international reserves and real interest rate. These independent variables, when needed, are transformed so that they become stationary and free from seasonal effects. All of them were obtained from IMF data according to the Special Data Dissemination Standard (SDDS).

Ordered probit versions of these three models are also estimated. The goal here is to discriminate between periods of high intensity crises (above two standard-deviations) from periods of medium intensity (between one and two standard-deviations):

$$C_{i,t}^{Currency} = \begin{cases} 2, & \text{if } C_{i,t}^{\text{FL}} > \overline{C_{i,t}^{\text{FL}}} + 2\sigma_{i,t} \\ 1, & \text{if } \overline{C_{i,t}^{\text{FL}}} + \sigma_{i,t} < C_{i,t}^{\text{FL}} \le \overline{C_{i,t}^{\text{FL}}} + 2\sigma_{i,t} \\ 0, & \text{otherwise.} \end{cases}$$

As in Coudert & Gex (2008), I assess the in sample predictive power of the estimated models with the probability cut-off set at 20%, above which a crisis is predicted by the model. I present the percentage of correctly predicted observations (crises and non-crises) divided by the total number of observations, the percentage of correctly predicted crises divided by the total number of crises and the percentage of correctly predicted by the total number of crises.

3 Results

Figure 1 shows the median behavior of the pressure indicator for currency crises C^{FL} as defined in equation (9), over the sample period from January 2007 to June 2018. The periods shaded in gray represent the two 12-month pre-crisis periods: July 2007 to June 2008 for the Subprime crisis and July 2010 to June 2011 for the European crisis. This indicator begins to rise before these crises, as expected.

Figure 2 illustrates the median behavior of the five risk aversion indicators for my sample of countries over the studied period. The indicators were standardized to enable comparability among them. The indicators are most sensitive to the Subprime crisis. As I am dealing with emerging markets, it is worth mentioning the Subprime crisis not only reached these markets later than the advanced economies, but also did it in different ways at the beginning (Mesquita & Torós, 2010).

The major reaction of the risk aversion indicators occurred at the end of 2008. ERP indicator decreased very fast at the end of that year but also increased very fast afterwards. The quantiles (dotted lines in this figure) revealed different behavior of the indicator among the countries. Brazil, India, Chile, Indonesia, Israel and Philippines exhibited the lowest ERP level in December 2008. VSU, MFVRP, ATMVRP and EPU indicators did not show this discrepant pattern appong countries when they detected the crisis.

Figure 1: Pressure indicator for currency crises



Notes: This figure shows the evolution of the median of the pressure indicators for Brazil, Chile, Colombia, India, Indonesia, Israel, Malaysia, Mexico, Russia, Singapore, South Africa, Thailand, Turkey and Philippines. Quantiles 0.25 and 0.75 are also presented. Gray columns identify the 12 months before the Subprime and the European crises.

Table 2 presents mean and standard-deviation of the five risk aversion indicators for all of the 14 countries.⁶ Statistics are evaluated for two segment periods: no crisis and pre-crisis (the 12 months period before a crisis is identified according to the definition used in this paper). Mean differences, defined by mean of the pre-crisis periods minus the mean of the no crisis periods, and its test statistic are also presented. The results in Table 2 confirm the mean of the risk aversion indicators is higher in the pre-crisis periods than in the normal periods.⁷

Table 2 also shows the cross correlation among the five risk aversion indicators. Considering all countries and the whole period, the risk aversion indicators are positively correlated. The exceptions are not statistically significant.

Table 3 presents the probit estimates for the three models used to predict currency crises. In Model 1, it can be seen the same control variables used in Coudert & Gex (2008) worked properly for my sample. Real exchange rate, international reserves and real interest rate were all significant at 1%. As expected, real exchange rate and international reserves have negative signs: an appreciation of the first and/or a fall of international reserves are supposed to increase the probability of a currency crisis. For real interest rate, the sign is also negative: its increase can lead to a lower probability of currency crises, since foreign capital inflow is stimulated.

⁶Evolution of the indicators for each country can be seen in Figure A-1 in the Appendix.

 $^{^{7}}$ MFVRP is the only exception, where its mean in the pre-crisis period is lower, but this difference is not statistically different from zero.

Figure 2: Risk aversion indicators



Notes: This figure depicts the evolution of the median of each risk aversion indicator for Brazil, Chile, Colombia, India, Indonesia, Israel, Malaysia, Mexico, Russia, Singapore, South Africa, Thailand, Turkey and Philippines. The indicators were standardized to enable comparability among them. Quantiles 0.25 and 0.75 are also presented. ERP is obtained from the difference between RND and RWD functions. VSU is based on the difference between the Black & Scholes (1973) and the Bakshi et al. (2003) implied volatilities. MFVRP is the difference between realized and model-free risk-neutral volatilities. ATMVRP is the difference between realized and at-the-money volatilities. EPU index is based on Baker et al. (2016).

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$				Mean	S.D.		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $			No crisis periods	-0.03	0.20		
$\frac{ERP}{VSU} = \frac{Mean difference}{test statistic} = \frac{0.03^{**}}{2.84} + \frac{1}{2.84} + \frac{1}{2.84$		EDD	Pre-crisis periods	0.01	0.03		
$\frac{\text{test statistic}}{\text{VSU}} = \frac{2.84}{\text{No crisis periods}} = 1.84 + 6.13}{\text{No crisis periods}} = 3.16 + 9.40}{\text{Mean difference}} = 1.32^{**} + 1 + 1.52^{**}$		EKP	Mean difference	0.03**			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			test statistic	2.84			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$			No crisis periods	1.84	6.13		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		VCU	Pre-crisis periods	3.16	9.40		
$ \begin{array}{c c c c c c c } & \mbox{test statistic} & 2.07 \\ \hline \mbox{MFVRP} & \mbox{No crisis periods} & -0.07 & 1.43 \\ \hline \mbox{Pre-crisis periods} & -0.10 & 2.42 \\ \hline \mbox{Mean difference} & -0.03 & & & & & & & & & & & & & & & & & & &$		VSU	Mean difference	1.32**			
$\begin{array}{c cccc} & & & & & & & & & & & & & & & & & $			test statistic	2.07			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			No crisis periods	-0.07	1.43		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		MEVDD	Pre-crisis periods	-0.10	2.42		
$ \begin{array}{c c c c c c c c } & test statistic & -0.17 \\ \hline & No crisis periods & -0.14 & 1.35 \\ Pre-crisis periods & 0.12 & 2.37 \\ \hline & Mean difference & 0.26^{**} \\ test statistic & 1.66 \\ \hline & & & & & & & & & & & & & & & & & &$		MFVKP	Mean difference	-0.03			
$\begin{array}{c ccccc} & & & & & & & & & & & & & & & & &$			test statistic	-0.17			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			No crisis periods	-0.14	1.35		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			Pre-crisis periods	0.12	2.37		
$\begin{tabular}{ c c c c c c } \hline test statistic & 1.66 \\ \hline No crisis periods & 11.01 & 32.71 \\ Pre-crisis periods & 17.67 & 45.59 \\ \hline Mean difference & 6.67** \\ test statistic & 2.08 \\ \hline \\ $		AIWIVKP	Mean difference	0.26**			
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$			test statistic	1.66			
EPU Pre-crisis periods Mean difference test statistic 17.67 6.67** 45.59 0.000 6.67** 6.67** 2.08 2.08 ERP 2.08 ERP VSU MFVRP ATMVRP ERP 1 VSU 16.99%*** MFVRP -0.41% 19.76%*** 1 ATMVRP -2.12% 6.29%*** 97.59%*** EPU -5.55%			No crisis periods	11.01	32.71		
LEPU Mean difference test statistic 6.67** Mean difference test statistic 2.08 ERP 2.08 ERP VSU MFVRP ATMVRP ERP 1 VSU 16.99%*** MFVRP -0.41% 19.76%*** 1 ATMVRP -2.12% 6.29%*** 97.59%*** EPU -5.55%		EDU	Pre-crisis periods	17.67	45.59		
test statistic 2.08 Cross correlations ERP ERP VSU MFVRP ATMVRP EPU VSU 16.99%*** 1 I I I MFVRP -0.41% 19.76%*** 1 I I ATMVRP -2.12% 6.29%*** 97.59%*** 1 EPU EPU -5.55% 11.36%*** 8.69%*** 7.63% 1		EPU	Mean difference	6.67**			
Cross correlations ERP VSU MFVRP ATMVRP EPU ERP 1			test statistic	2.08			
Cross correlations ERP VSU MFVRP ATMVRP EPU ERP 1							
ERP VSU MFVRP ATMVRP EPU ERP 1			Cross correlations				
ERP 1 VSU 16.99%*** 1 MFVRP -0.41% 19.76%*** 1 ATMVRP -2.12% 6.29%*** 97.59%*** 1 EPU -5.55% 11.36%*** 8.69%*** 7.63% 1		ERP	VSU	MFVRP	P ATM	1VRP	EPU
VSU 16.99%*** 1 MFVRP -0.41% 19.76%*** 1 ATMVRP -2.12% 6.29%*** 97.59%*** 1 EPU -5.55% 11.36%*** 8.69%*** 7.63% 1	ERP	1					
MFVRP -0.41% 19.76%*** 1 ATMVRP -2.12% 6.29%*** 97.59%*** 1 EPU -5.55% 11.36%*** 8.69%*** 7.63% 1	VSU	16.99%***	1				
ATMVRP-2.12%6.29%***97.59%***1EPU-5.55%11.36%***8.69%***7.63%1	MFVRP	-0.41%	19.76%***	1			
EPU -5.55% 11.36%*** 8.69%*** 7.63% 1	ATMVRP	-2.12%	6.29%***	97.59%**	**	1	
	EPU	-5.55%	11.36%***	8.69%**	* 7.6	53%	1

Table 2: Summary statistics for risk aversion indicators and cross correlations

Notes: This table presents a mean comparison of the risk aversion indicators for all of the 14 countries between the months with no crisis and the 12 months before a crisis. Standard-deviations (S.D.) for each indicator are also presented. Cross correlations among the five indicators are also presented, considering the whole period. Significance: *** = 1%, **=5% and *=10%.

	Model 1			Model 2					Model 3		
		ERP	NSU	MFVRP	ATMVRP	EPU	ERP	VSU	MFVRP	ATMVRP	EPU
Constant	-1.0213	-1.0422	-1.0591	-1.0760	-1.0703	-1.0345	-0.9861	-1.0222	-1.0544	-1.0465	-0.9866
	$(0.0360)^{***}$	$(0.0381)^{***}$	$(0.0374)^{***}$	$(0.0383)^{***}$	$(0.0381)^{***}$	$(0.0366)^{***}$	$(0.0359)^{***}$	$(0.0358)^{***}$	$(0.0369)^{***}$	$(0.0366)^{***}$	$(0.0346)^{***}$
Real exchange rate	-0.2900	-0.3268	-0.2649	-0.2363	-0.2680	-0.3261					
	$(0.1046)^{***}$	$(0.1108)^{***}$	$(0.1083)^{**}$	$(0.1205)^{*}$	$(0.1202)^{**}$	$(0.1036)^{***}$					
Reserves	-0.3234	-0.3329	-0.2491	-0.3018	-0.3055	-0.2126					
	$(0.0370)^{***}$	$(0.0381)^{***}$	$(0.0417)^{**}$	$(0.0416)^{***}$	$(0.0415)^{***}$	$(0.0375)^{***}$					
Real interest rate	-0.2092	-0.2287	-0.2301	-0.2201	-0.2125	-0.2126					
	$(0.0358)^{***}$	$(0.0370)^{***}$	$(0.0378)^{***}$	$(0.0399)^{***}$	$(0.0392)^{***}$	$(0.0359)^{***}$					
Risk aversion indicator		1.8388	0.1126	0.1674	0.1232	-0.1675	1.7375	0.2011	0.1909	0.1407	-0.1900
		$(0.3239)^{**}$	$(0.0361)^{***}$	$(0.0353)^{***}$	$(0.0349)^{***}$	$(0.0392)^{***}$	$(0.3130)^{***}$	$(0.0326)^{***}$	$(0.0348)^{***}$	$(0.0345)^{***}$	$(0.0374)^{***}$
McFadden R-squared	0.0576	0.0880	0.0639	0.0673	0.0604	0.0686	0.0284	0.0231	0.0059	0.0100	0.0156
Log likelihood	-813.36	-780.53	-750.67	-701.96	-707.10	-803.85	-813.30	-787.71	-715.38	-722.34	-855.27
Prob(LR statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
% correctly predicted - Total	69.2%	68.7%	73.7%	77.2%	76.1%	68.5%	66.0%	79.1%	81.3%	82.4%	70.7%
% correctly predicted - Crises	44.8%	53.0%	41.4%	38.2%	35.6%	46.4%	31.97%	28.4%	15.7%	10.8%	32.0%
% correctly predicted - Non Crises	74.1%	71.8%	79.8%	84.1%	83.2%	73.0%	72.8%	88.6%	92.8%	95.0%	78.4%
9 Total obs.	1918	1896	1839	1781	1781	1918	1908	1848	1932	1781	1781
	Notes: T	his table presents 1	the coefficients of	the probit regressic	ons on the currenc	y crisis indicator,	considering three 1	models: (1) contro	1		
	variables	only, (2) controls p	dus one of the five	risk aversion indica	ators and (3) risk a	resion indicator or	lly. Standard-errors	s are in parentheses			
	Significa	nce: *** = 1%, **=	5% and *=10%. P	obability of more t	than 20% is the cri	erion used to defin	e predicted crisis.				

Table 3: Probit regression for currency crisis

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When risk aversion indicators are incorporated in the base model (Model 2), they are significant and exhibit expected positive signs; the only exception is the EPU index's negative sign. The same results are also obtained even when the risk aversion indicators are taken alone, as in Model 3. The unexpected negative sign of EPU index may be associated with the fact that it is an index that focuses more on what has happened than on what is expected. Besides, I had to use its global version for many countries, because this index is not available for 6 out of the 14 emerging countries under analysis (Turkey, Malaysia, Indonesia, Israel, Philippines and Thailand).

In terms of regression's quality, ERP indicator improves more McFadden pseudo R2 than the other indexes, when it is added to the base model. All of the models exhibit zero p-value LR statistic, meaning the joint null hypothesis that all slope coefficients, except the constant, are zero is rejected. ERP is also the only indicator that improves the predictive power of the base model in terms of correctly predicted crises.

The ordered probit models' results (Table 4) are similar to their corresponding plain specification in terms of significance and sign of the dependent variables. The same controls and the five risk indexes worked well to predict medium and high currency crises as defined in the Methodology section.

Results in terms of predictive power are also similar to those in Coudert & Gex (2008). Overall, the ordered model predicts fewer currency crises when they are discriminated between medium and high intensity ones. When I introduce a risk aversion indicator (Model 2 compared to Model 1 in Table 4), it improves the model's capacity to predict medium and high crises. When taken alone (Model 3), the predictive capacity of all risk indicators is nil.

Table 4: Ordered probit regression for currency crisis

	Model 1			Model 2					Model 3		
	T TODOTT	EDD	11ST	MEVDD		EDL	EDD	VCI1	MEVDD	ATMAVDD	EDII
Real evchange rate	-0.2626	-0 2733	0.80 -0.778	1017 VNF -0 2266	AI M VKF -0 2447	-0.2974	ENT	000		ALMVR	EFU
	0.02020	CC 12:0	07/2/0 /// 08/2)***	(0.0046)**	(0 00 45)**	+ (0,000)					
I	$(c+on\cdot n)$	(0+00.0)	(7+00.0)	$(n+\epsilon n,n)$	(0+00)	(6700.0)					
Reserves	-0.0925	-0.1000	-0.0669	-0.0673	-0.0671	-0.0911					
	$(0.0263)^{***}$	$(0.0266)^{***}$	$(0.0274)^{**}$	$(0.0282)^{**}$	$(0.0281)^{**}$	$(0.0264)^{***}$					
Real interest rate	-0.2377	-0.2423	-0.2644	-0.2495	-0.2448	-0.2457					
	$(0.0279)^{***}$	$(0.0282)^{***}$	$(0.0288)^{***}$	$(0.0298)^{***}$	$(0.0298)^{***}$	$(0.0280)^{***}$					
Risk aversion indicator		0.3315	0.0682	0.1413	0.1117	-0.1934	0.2987	0.0748	0.1618	0.1304	-0.1676
		$(0.1292)^{***}$	$(0.0274)^{**}$	$(0.0286)^{***}$	$(0.0284)^{***}$	$(0.0281)^{***}$	$(0.1279)^{**}$	$(0.0269)^{***}$	$(0.0280)^{***}$	$(0.0277)^{***}$	$(0.0274)^{***}$
Limit 1	0.0030	-0.0138	-0.0060	0.0047	0.0058	0.0024	-0.0122	-0.0112	-0.002	-0.0013	0.0058
	(0.0289)	(0.0293)	(0.0297)	(0.0302)	(0.0302)	(0.0291)	(0.0288)	(0.0291)	(0.0298)	(0.0297)	(0.0286)
Limit 2	0.9992	0.9933	1.0475	1.0824	1.0792	1.0156	0.9612	1.0048	1.0490	1.0448	0.9825
	$(0.0346)^{***}$	$(0.0350)^{***}$	$(0.0361)^{***}$	$(0.0373)^{***}$	$(0.0377)^{***}$	$(0.0350)^{***}$	$(0.0342)^{***}$	$(0.0352)^{***}$	$(0.0366)^{***}$	$(0.0365)^{***}$	$(0.0342)^{***}$
Pseudo R-squared	0.0228	0.0259	0.0290	0.0304	0.0278	0.0352	0.0014	0.0021	0.0095	0.0062	0.0089
Log likelihood	-1895.07	-18671.17	-1797.27	-1724.35.100	-1728.94	-1870.72	-1929.30	-1856.10	-1761.51	-1767.40	-1932.68
Prob(LR statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
% correctly predicted - Non crises	94.7%	92.4%	90.7%	88.4%	89.8%	90.1%	100.0%	98.8%	96.2%	97.6%	100.0%
26 correctly predicted - Median crises	7.6%	11.2%	16.3%	15.3%	14.1%	17.0%	0.0%	0.0%	2.4%	1.9%	0.0%
$^{\infty}_{\infty}$ correctly predicted - High crises	2.2%	2.2%	3.1%	3.4%	2.6%	3.4%	0.0%	0.0%	1.5%	0.7%	0.0%
Total obs.	1918	1896	1839	1918	1781	1781	1908	1848	1781	1781	1932
	Notes: Thi	s table presents the	e coefficients of th	e ordered probit reg	gressions on the ci	urrency crisis indic	ator, considering	three models: (1)			
	control var	iables only, (2) cor	ntrols plus one of	the five risk aversio	on indicators and (3) risk aversion in	dicator only. Stan	dard-errors are in			
	parenthese	s. Significance: ***	* = 1%, **=5% and	*=10%. The order	ed probit discrimin	ates high intensity	(above two standa	d-deviations) and			
	medium int	ensity crises (betwo	een one and two st	andard-deviations).							

I conduct an out-of-sample exercise for a restricted period, the 2010-2011 European crisis, since the crises of my sample are mostly concentrated in this year. There are hardly any crises at the end of my sample period. Therefore, to check if the models were able to predict out-of-sample crises, my estimation sample begins in January 2007 and ends in June 2010, so I can compute the probability of a currency crisis in the following 12 months. As Bussiere & Fratzscher (2006) observe, this is not strictly out-of-sampling, since some included variables may not be significant, whereas other excluded variables may have been significant for the shorter out-of-sample model periods. The reason for restricting the model to the same variables is to obtain a comparison between in-sample and out-of-sample performances of the benchmark model. The important question is whether the model would have predicted the European crisis in 2010-2011, even though some of the control variables could not yet be identified as significant factors.

Model 2 - Empirical Risk Premium is the model used for out-of-sample forecasting, as it is the one with the best performance in terms of goodness of fit: the lowest RMSE and the fewest number of prediction errors (no type I errors, or 'wrong signs', and only 2 type II errors, or 'false alarms').

Table 5 shows the predicted probabilities of a crisis 12 months ahead of June 2010 in the first column. The second column indicates the starting point of the crisis. For 10 out of 14 countries, predicted probabilities worked well to correctly forecast what happened 12 months afterward. For Chile, India, Indonesia, Israel, Malaysia, Mexico, Singapore and South Africa probabilities are above 20%, clearly signaling an imminent crisis, which actually occurred. For Russia and Thailand, probabilities are below 20% in June 2010 and there were no crises in the following 12 months. For Brazil, Colombia, Turkey and Philippines, there are false alarms, or more precisely, the model predicted a crisis in the 12 months period ahead but it did not happen. Most importantly, there are no wrong signs detected, or equivalently, failure to predict a crisis that occurred. Therefore, the model performed well, even outside the sample, predicting most of the emerging market currency crises occurring in the wake of the European crisis.

Country	Predicted probability of crisis in June 2010	Crisis 12 months later
Brazil	21.22%	No
Chile	33.80%	Yes: Sep 2010
Colombia	20.89%	No
India	35.12%	Yes: Sep 2010
Indonesia	23.73%	Yes: Sep 2010
Israel	26.36%	Yes: Nov 2010
Malaysia	23.95%	Yes: Sep 2010
Mexico	24.70%	Yes: Sep 2010
Philippines	27.95%	No
Russia	9.63%	No
Singapore	29.20%	Yes: Sep 2010
South Africa	28.94%	Yes: Sep 2010
Thailand	2.34%	No
Turkey	24.10%	No

Table 5: Predicted probabilities, out-of-sample forecasts

Notes: This table presents probabilities of a currency crisis as of June 2010 within the 12 following months. The probabilities are predicted by the Model 2 - ERP version estimated until June 2010 only (estimation sample). Probability of more than 20% is the criterion used to define predicted crisis.

I test other estimations considering different c_{risis}^{19} horizons (three and six months). The results in

general support the conclusions just presented (Tables A.1 and A.2 in the Appendix). As an additional robustness check of the results, I re-estimate the panel probit models with random effects and a logit version of them in order to consider fixed effects. The results are virtually the same (Tables A.3 and A.4). This suggests ignoring country-specific information does not constitute a bias in my estimation.

4 Conclusion

As financial crises generally coincide with periods in which risk aversion increases, it is not unusual to find papers that incorporate risk aversion indicators in economic models to predict these crises. However, they usually deal with these indicators built in a backward-looking way, estimated from historical time series data.

Risk aversion indicators based on option prices are forward-looking and therefore have the advantage of gathering a wide range of simultaneous information related to expectations of financial, economic and political variables at a single point in time. This paper tries to check whether indicators extracted from options rise just before the crises and also whether they are able to forecast crises. To this end, I incorporate these types of indicators in probit models for currency crisis probabilities based on traditionally used economic control variables.

The results show option-based risk aversion indicators are significant to predict currency crises and are positively related to the probabilities of occurring these crises in a one-year horizon in all tested models. With respect to their predictive power, Empirical Risk Premium index (ERP) improves the prediction made by the usual economic control variables, which are the real exchange rate, the official international reserves and the real interest rate. ERP added to these controls performs well even outside the sample, predicting most of the emerging market currency crises occurring in the wake of the European crisis.

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	Model 1			Model 2					Model 3		
		ERP	VSU	MFVRP	ATMVRP	EPU	ERP	NSU	MFVRP	ATMVRP	EPU
Constant	-1.6193	-1.6506	-1.6548	-1.6585	-1.6433	-1.6363	-1.5220	-1.5688	-1.5868	-1.5868	-1.5140
	$(0.0507)^{***}$	$(0.0549)^{***}$	$(0.0540)^{***}$	$(0.0549)^{***}$	(0.0540) ***	$(0.0517)^{***}$	$(0.0471)^{***}$	$(0.0486)^{***}$	$(0.0496)^{***}$	$(0.0490)^{***}$	$(0.0445)^{***}$
Real exchange rate	-0.6043	-0.6658	-0.5410	-0.4851	-0.5235	-0.6196					
1	$(0.1272)^{***}$	$(0.1349)^{***}$	$(0.1287)^{***}$	$(0.1472)^{***}$	$(0.1468)^{***}$	$(0.1269)^{***}$					
Reserves	-0.2574	-0.2714	-0.1527	-0.2492	-0.2559	-0.2752					
	$(0.0487)^{***}$	$(0.0500)^{***}$	$(0.0547)^{**}$	$(0.0535)^{***}$	(0.0541) ***	$(0.0499)^{***}$					
Real interest rate	-0.2990	-0.3023	-0.2856	-0.2930	-0.2927	-0.3030					
	$(0.0485)^{***}$	$(0.0497)^{***}$	$(0.0512)^{***}$	$(0.0418)^{***}$	$(0.0530)^{***}$	$(0.0492)^{***}$					
Risk aversion indicator		1.7143	0.2505	0.2568	0.2130	0.1311	1.4993	0.3141	0.3023	0.2436	0.1126
24		(0.4595)***	$(0.0429)^{***}$	$(0.0418)^{***}$	$(0.0407)^{***}$	$(0.0457)^{***}$	(0.4307) ***	$(0.0380)^{***}$	$(0.0404)^{***}$	$(0.0396)^{***}$	$(0.0421)^{***}$
McFadden R-squared	0.0896	0.1134	0.1347	0.1339	0.1206	0.1032	0.0210	0.0732	0.0683	0.0457	0.0073
Log likelihood	-425.59	-413.08	-395.16	-369.20	-374.85	-419.20	-459.55	-426.29	-397.15	-396.52	-467.60
Prob(LR statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
% correctly predicted - Total	91.9%	91.7%	91.8%	92.5%	92.4%	91.8%	91.9%	92.3%	93.0%	93.4%	93.4%
% correctly predicted - Crises	18.1%	22.5%	24.0%	24.3%	25.2%	18.9%	0.0%	11.9%	13.0%	7.2%	0.0%
% correctly predicted - Non Crises	97.2%	96.7%	96.7%	97.1%	97.0%	96.9%	100.0%	97.7%	98.6%	99.2%	100.0%
Total obs.	1918	1896	1839	1781	1781	1918	1908	1848	1781	1781	1932
	Notes: T	This table presents th	ne coefficients of the	e probit regression	s on the currency cr	sis indicator for the	e following 3 month	is, considering three	0		
	models:	(1) control variables	s only, (2) controls	plus one of the thre	e risk aversion indi	cators and (3) risk a	iversion indicator of	nly. Standard-errors	s		

are in parentheses. Significance: *** = 1%, **=5% and *=10%. Probability of more than 20\% is the criterion used to define predicted crisis.

Table A.1: Probit regression for currency crisis - three-month horizon

6 Appendix

	Model 1			Model 2					Model 3		
		ERP	NSU	MFVRP	ATMVRP	EPU	ERP	NSU	MFVRP	ATMVRP	EPU
Constant	-1.2802	-1.2969	-1.2971	-1.3104	-1.2993	-1.2810	-1.2251	-1.2508	-1.2753	-1.2610	-1.2142
	$(0.0409)^{***}$	$(0.0430)^{***}$	$(0.0425)^{***}$	(0.0436)	$(0.0428)^{***}$	$(0.0407)^{***}$	$(0.0396)^{***}$	$(0.0402)^{***}$	$(0.0411)^{***}$	$(0.0405)^{***}$	$(0.0376)^{***}$
Real exchange rate	-0.3643	-0.3951	-0.3307	-0.3131	-0.3520	-0.3704					
	$(0.1123)^{***}$	$(0.1183)^{***}$	$(0.1140)^{***}$	$(0.1297)^{**}$	$(0.1298)^{***}$	$(0.1106)^{***}$					
Reserves	-0.2706	-0.2834	-0.1805	-0.2523	-0.2573	-0.2741					
	$(0.0410)^{***}$	$(0.0421)^{***}$	$(0.0463)^{***}$	$(0.0458)^{***}$	$(0.0456)^{***}$	$(0.0415)^{***}$					
Real interest rate	-0.2613	-0.2640	-0.2553	-0.2473	-0.2505	-0.2609					
	$(0.0406)^{***}$	$(0.0417)^{***}$	$(0.0427)^{***}$	$(0.0445)^{***}$	$(0.0446)^{***}$	$(0.0407)^{***}$					
Risk aversion indicator		1.6064	0.2158	0.2227	0.1707	0.0212	1.4951	0.2838	0.2531	0.1972	0.0028
		$(0.3546)^{***}$	$(0.0387)^{***}$	$(0.0380)^{***}$	$(0.0371)^{***}$	(0.0398)	$(0.3398)^{***}$	$(0.0345)^{***}$	$(0.0371)^{***}$	$(0.0362)^{***}$	(0.0376)
McFadden R-squared	0.0610	0.0844	0.0916	0.0864	0.0750	0.0621	0.0220	0.0504	0.0397	0.0246	0.0000
Log likelihood	-633.80	-615.61	-595.20	-556.27	-563.23	-633.06	-660.97	-625.17	-584.73	-593.91	-678.77
Prob(LR statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93
% correctly predicted - Total	84.8%	83.7%	85.1%	86.1%	86.0%	84.6%	88.6%	86.4%	88.1%	88.3%	88.7%
% correctly predicted - Crises	22.7%	26.3%	34.1%	28.1%	24.4%	23.1%	0.0%	19.8%	14.6%	9.3%	0.0%
% correctly predicted - Non Crises	92.7%	91.1%	91.7%	93.1%	93.4%	92.4%	100.0%	95.0%	96.9%	97.8%	100.0%
55 Total obs.	1918	1896	1839	1781	1781	1918	1908	1848	1781	1781	1932
	Notes: T	his table presents th	e coefficients of the	probit regressions	on the currency cri	sis indicator for the	following 6 month	s, considering three			
	models:	(1) control variables	: only, (2) controls I	lus one of the three	e risk aversion indic	ators and (3) risk a	version indicator or	uly. Standard-error:			
	are in pa	entheses. Significal	nce: *** = 1%, **=	5% and *=10%. P	robability of more	than 20% is the cri	terion used to defin	le predicted crisis.			

Table A.2: Probit regression for currency crisis - six-month horizon

	Model 1			Model 2					Model 3		
		ERP	NSU	MFVRP	ATMVRP	EPU	ERP	NSU	MFVRP	ATMVRP	EPU
Constant	-1.2322	-1.2526	-1.3361	-1.5314	-1.5135	-1.2587	-1.1576	-1.2751	-1.4985	-1.4752	-1.1818
	$(0.1857)^{***}$	$(0.1567)^{***}$	$(0.2152)^{***}$	$(0.2988)^{***}$	$(0.2934)^{***}$	$(0.1932)^{***}$	$(0.1357)^{***}$	$(0.2013)^{***}$	$(0.2922)^{***}$	$(0.2854)^{***}$	$(0.1779)^{***}$
Real exchange rate	-0.2331	-0.2606	-0.1871	-0.2544	-0.2970	-0.2839					
	$(0.1027)^{**}$	$(0.1089)^{**}$	$(0.1144)^{*}$	$(0.1317)^{*}$	$(0.1212)^{**}$	$(0.1034)^{***}$					
Reserves	-0.3238	-0.3320	-0.2470	-0.2599	-0.2659	-0.3055					
	$(0.0392)^{***}$	$(0.0398)^{***}$	$(0.0452)^{***}$	$(0.4589)^{***}$	$(0.0456)^{***}$	$(0.0396)^{***}$					
Real interest rate	-0.2232	-0.2392	-0.2623	-0.2365	-0.2389	-0.2341					
	$(0.0378)^{***}$	(0.0385)***	$(0.0409)^{***}$	$(0.0437)^{***}$	$(0.0434)^{***}$	$(0.0381)^{***}$					
Risk aversion indicator		4.001	0.1549	0.1904	0.1293	-0.1751	3.0942	0.2334	0.2195	0.1537	-0.1836
		$(1.5642)^{**}$	$(0.0386)^{***}$	$(0.0401)^{***}$	$(0.0393)^{***}$	$(0.0416)^{***}$	$(1.1439)^{***}$	$(0.0352)^{***}$	$(0.0393)^{***}$	$(0.0387)^{***}$	$(0.0396)^{***}$
Log likelihood	-748.98	-734.13	-671.83	-610.47	-616.53	-739.67	-781.83	-702.93	-638.09	-646.12	-782.94
Prob(LR statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total obs.	1931	1918	1885	1781	1781	1931	1919	1856	1781	1781	1932
		Notes: This table	presents the coeffic	cients of the probit	regressions with ran	idom effects on the	currency crisis indi	cator, considering th	ree		
		models:: (1) contro	ol variables only, (2)) controls plus one o	f the five risk aversio	in indicators and (3)	isk aversion indicat	or only. Standard-eri	Ors.		
26		are in parentheses.	Significance: *** =	= 1%, **=5% and *-	=10%. Probability of	f more than 20% is the	ne criterion used to	define predicted crisi	s.		

Table A.3: Probit regression for currency crisis - random effects

	Model 1			Model 2					Model 3		
		ERP	NSU	MFVRP	ATMVRP	EPU	ERP	NSU	MFVRP	ATMVRP	EPU
Real exchange rate	-0.4476	-0.4916	-0.3618	-0.4686	-0.5377	-0.5282					
	$(0.1854)^{**}$	$(0.1944)^{**}$	$(0.2087)^{*}$	$(0.2286)^{**}$	$(0.2280)^{**}$	$(0.1874)^{***}$					
Reserves	-0.5292	-0.5514	-0.3984	-0.4247	-0.4321	-0.4982					
	$(0.0692)^{***}$	$(0.0705)^{***}$	(0.0799)***	$(0.0803)^{***}$	$(0.0800)^{***}$	$(0.0696)^{***}$					
Real interest rate	-0.3929	-0.4330	-0.4633	-0.4082	-0.4127	-0.4170					
	$(0.0668)^{***}$	$(0.0687)^{***}$	$(0.0730)^{***}$	$(0.0777)^{***}$	$(0.0773)^{***}$	$(0.0670)^{***}$					
Risk aversion indicator		15.7203	0.2679	0.3214	0.2207	-0.3193	6.3583	0.3969	0.3752	0.2675	-0.3223
		$(6.1937)^{**}$	$(0.0685)^{***}$	$(0.0702)^{***}$	$(0.0670)^{***}$	$(0.0758)^{***}$	(5.7462)	$(0.0627)^{***}$	$(0.0685)^{***}$	$(0.0663)^{***}$	$(0.0726)^{***}$
Log likelihood	-693.85	-682.72	-617.70	-557.81	-563.48	-684.19	-729.20	-647.65	-584.23	-591.84	-725.83
Prob(LR statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00
Total obs.	1656	1644	1581	1283	1283	1656	1644	1581	1283	1283	1656
		Notes: This table pr	esents the coefficient	ts of the probit regre	ssions with fixed effe	cts on the currency c	risis indicator, c	onsidering three mo-	dels::		
		(1) control variables	s only, (2) controls p	lus one of the five r	isk aversion indicato	rs and (3) risk avers	on indicator on	ly. Standard-errors a	tre in		
		parentheses. Signifi	cance: *** = 1%, **	≔5% and *=10%. P	robability of more th	an 20% is the criteri	n used to defin	e predicted crisis.			

Table A.4: Logit regression for currency crisis - fixed effects



Figure A.1: Risk aversion indicators per country

Notes: This figure depicts the evolution of the five risk aversion indicators per country. ERP is obtained from the difference between RND and RWD functions. VSU is based on the difference between the Black & Scholes (1973) and the Bakshi et al. (2003) implied volatilities. MFVRP is the difference between realized and model-free risk-neutral volatilities. ATMVRP is the difference between realized and at-the-money volatilities. EPU index is based on Baker et al. (2016).