No 2007 – 02
January

Does Risk Aversion Drive Financial Crises?
Testing the Predictive power of Empirical Indicators

Virginie Coudert
Mathieu Gex

Does Risk Aversion Drive Financial Crises?
Testing the Predictive power of Empirical Indicators

Virginie Coudert
Mathieu Gex

No 2007 – 02
January

TABLE OF CONTENTS

Summary ... **3**

Abstract ... **5**

Résumé ... **6**

Résumé court ... **8**

SUMMARY ... **5**

ABSTRACT ... **6**

RÉSUMÉ ... **7**

1. INTRODUCTION ... **9**

2. THEORETICAL FRAMEWORK ... **10**

2.1 Risk aversion in the CCAPM ... 10
2.2 Consistency with the CAPM ... 12
2.3 Consistency with factor models ... 14

3. THE RISK AVERSION INDICATORS ... **14**

3.1 Indicators of the GRAI type ... 14
3.2 A PCA indicator ... 16
3.3 Simple and aggregated indicators: the VIX and the LCVI ... 17
3.4 Other measures: the ICI ... 18
3.5 Comparison of the indicators ... 18

4. TESTING THE PREDICTIVE POWER OF THE INDICATORS ... **19**

4.1 Definition of currency crises ... 19
4.3 The dependent variable ... 22
4.4 The models used ... 22
4.5 Assessing the predictive power ... 23

5. FORECASTING OF CURRENCY CRISES ... **24**

5.1 Significance of the control variables and the risk aversion indicators ... 24
5.2 Predictive power for currency crises ... 24

6. FORECASTING OF STOCK MARKET CRISES ... **25**

6.1 Significance of the control variables and the risk aversion indicators ... 25
6.2 Predictive power for stock market crises ... 25
6.3 Can stock market reversals be predicted? ... 26

7. CONCLUSION ... **27**

References..28

Appendix 1: the database 38

Appendix 2: risk aversion indicators graphs...40

Appendix 3: currency and stock market crises 41

List of Working Papers released by CEPII..47

DOES RISK AVERSION DRIVE FINANCIAL CRISES? TESTING THE PREDICTIVE POWER OF EMPIRICAL INDICATORS

NON-TECHNICAL SUMMARY

Financial institutions often refer to empirical risk aversion indicators to gauge investors' market sentiment. Fluctuations in risk aversion are generally considered as a factor explaining crises. Periods of strong risk appetite can create speculative bubbles on financial prices, building up vulnerabilities. Then a sudden reversal in risk aversion may trigger sharp falls in asset prices and prompt a financial crisis.

A crucial point is to clearly define the concept of risk aversion. In the framework of asset pricing models, more precisely the Consumption CAPM (CCAPM), a risk premium can be decomposed into a "price of risk", which is common to all assets, and a "quantity of risk", which is specific to each asset. The empirical indicators of risk aversion used by financial institutions aim at assessing this "price of risk".

Those empirical indicators can be put together in four main groups. 1) The indicators of the GRAI (Global Risk Aversion Index) type are based on the idea that an increase in risk aversion should lead to a rise in risk premia across all markets, but the rise should be greater on the riskiest markets (Persaud, 1996, Kumar and Persaud, 2002). By using the CAPM, regarded as a special case of the CCAPM, this idea amounts to assessing changes in risk aversion as the correlation between price changes and their volatility. 2) Risk aversion can also be estimated as the common factor driving risk premia. This common factor can be evaluated through a factor analysis such as the Principal Component Analysis (PCA). 3) Some financial institutions also use raw series, as the VIX which is the implied volatility on the S&P 500, or combinations of raw series. 4) There are also other indicators, such as the State Street's one which does not fall into the previous categories.

In order to assess the relevance of all these empirical indicators, we investigate their ability to forecast exchange rate and stock market crises, by constructing "early warning signals" of crises. We use logit and multilogit models that link a qualitative variable representing crises to a set of quantitative exogenous variables. In a first model, the explanatory variables are the usual ones found in the economic literature. In a second model we add risk aversion indicators to these control variables. In a third one, risk aversion indicators are taken as the only explicative variable.

The results show that most of the considered risk aversion indicators have the expected positive sign and are significant in the regressions. Moreover, in the multilogit models, risk aversion remains high during the months following the crisis. As regard to their predictive power, which is tested in-the-sample, the results are quite different according to the type of crises. For currency crises, the indicators barely improve the prediction made by the usual control variables. By contrast, in the case of stock market crises, most indicators yield satisfactory results. The best predicting performances are obtained by a principal component analysis on risk premia.

ABSTRACT

Financial institutions often refer to empirical risk aversion indicators to gauge investors' market sentiment. These indicators, which are estimated in diverse ways, often show differing developments, although it is not possible to directly assess which is the most appropriate. Here, we consider the most well-known of these indicators and construct others with standard methods. As financial crises generally coincide with periods in which risk aversion increases, we try to check if these indicators rise just before the crises and also if they are able to forecast crises. We estimate logit and multilogit models of financial crises – exchange rate and stock market crises – using control variables and each of the risk aversion indicators. In-sample simulations allow us to assess their respective predictive powers. Risk aversion indicators are found to be good leading indicators of stock market crises, but less so for currency crises.

JEL Classification: C33, E44, F37, G12.

Keywords: Risk aversion; Leading indicators of crises, Currency crises, Stock market crises, Crises prediction.

L'AVERSION POUR LE RISQUE EXPLIQUE-T-ELLE LES CRISES FINANCIERES ? UN TEST SUR LA CAPACITÉ PRÉDICITVE DES INDICATEURS EMPIRIQUES

RÉSUMÉ NON TECHNIQUE

De nombreuses institutions financières utilisent des indicateurs d'aversion pour le risque pour évaluer l'humeur des investisseurs. Les fluctuations de l'aversion pour le risque sont souvent considérées comme un facteur explicatif des crises. Les périodes de fort appétit pour le risque peuvent être à l'origine de bulles spéculatives sur le prix des actifs financiers, créant ainsi des vulnérabilités. Un effondrement brutal de l'optimisme des investisseurs peut ensuite conduire à une forte baisse des prix et provoquer une crise financière.

Un point déterminant consiste à définir clairement le concept d'aversion pour le risque. Le cadre théorique fourni par les modèles de détermination des prix d'actifs, et plus précisément le *Consumption* CAPM (CCAPM), permet de décomposer une prime de risque en un « prix du risque », commun à tous les actifs, et une « quantité de risque », spécifique à chaque actif. Les différents indicateurs que nous utilisons dans ce papier cherchent à évaluer ce « prix du risque ».

Ces indicateurs empiriques peuvent être classés en quatre groupes. 1) Les indicateurs de type GRAI (*Global Risk Aversion Index*) sont basés sur l'idée qu'une augmentation de l'aversion pour le risque devrait conduire à une augmentation des primes de risque sur tous les marchés, cependant cette augmentation devrait être plus importante sur les marchés les plus risqués (Persaud, 1996, Kumar et Persaud, 2002). En utilisant le CAPM, considéré comme un cas particulier du CCAPM, cette idée revient à mesurer les évolutions de l'aversion pour le risque à travers la corrélation entre les variations de prix et les volatilités de ces variations sur un panel de différents actifs. 2) Il est possible d'estimer l'aversion pour le risque comme le facteur commun à un ensemble de primes de risque. Une analyse factorielle, telle que l'Analyse en Composantes Principales (ACP) permet de mesurer ce facteur commun. 3) Quelques institutions financières utilisent également des séries brutes, comme le VIX, qui est égal à la volatilité implicite sur le S&P 500, ou des combinaisons de séries brutes. 4) D'autres indicateurs, comme celui de State Street, n'entrent dans aucune des catégories précédentes.

Pour juger de la pertinence de ces indicateurs empiriques, nous nous intéressons à leur capacité à prévoir les crises de change et les crises boursières, en construisant des « indicateurs avancés » de crise. Nous utilisons des modèles logit et multilogit qui relient une variable qualitative représentant la crise à un ensemble de variables quantitatives. Un premier modèle retient pour variables explicatives les variables habituelles trouvées dans la littérature économique. Dans un second modèle, nous ajoutons les indicateurs d'aversion pour le risque à ces variables de contrôle. Dans un troisième modèle, les indicateurs d'aversion pour le risque sont utilisés comme seules variables explicatives.

Les résultats montrent que la plupart des indicateurs considérés ont le signe positif attendu et sont significatifs dans les régressions. De plus, dans les modèles multilogit, l'aversion pour le risque reste élevée durant les mois suivant la crise. Concernant leur pouvoir prédictif, qui est testé ici à l'intérieur de l'échantillon, les résultats sont différents selon le type de crise. Pour les crises de change, les indicateurs améliorent à peine les prévisions obtenues avec les variables de contrôle habituelles. Dans le cas des crises boursières, la plupart des indicateurs donnent des résultats satisfaisants. Les meilleures performances sont obtenues par une ACP sur les primes de risque.

RÉSUMÉ

De nombreuses institutions financières utilisent des indicateurs d'aversion pour le risque pour évaluer l'humeur des investisseurs. Ces indicateurs, estimés de différentes façons, présentent souvent des évolutions hétérogènes sans qu'il soit possible de les départager directement. Ici, nous étudions les indicateurs empiriques les plus souvent utilisés et en construisons d'autres à partir des méthodes les plus connues. Les crises financières coïncident généralement avec les périodes durant lesquelles l'aversion pour le risque augmente. Nous essayons donc de voir si ces indicateurs connaissent une hausse juste avant les crises et également s'ils permettent de prédire ces crises. Nous estimons des modèles logit et multilogit des crises financières – crises de change et crises boursières – en utilisant des variables de contrôle. Les simulations réalisées sur notre échantillon nous permettent d'évaluer leur pouvoir prédictif respectif. Les résultats obtenus incitent à conclure que les indicateurs d'aversion pour le risque sont de bons indicateurs avancés des crises boursières, beaucoup moins pour les crises de change.

Classement JEL : C33, E44, F37, G12.

Mots Clés : Aversion pour le risque, Indicateurs avancés de crise, crises de change, crises boursières; prévision de crise.

DOES RISK AVERSION DRIVE FINANCIAL CRISES? TESTING THE PREDICTIVE POWER OF EMPIRICAL INDICATORS

Virginie Coudert[1], *Mathieu Gex*[2]

1. INTRODUCTION

Fluctuations in investor risk aversion are often cited as a factor to explain crises on financial markets. The alternation between periods of optimism prompting investors to make risky investments, and periods of pessimism, when they retreat to the safest forms of investments, could be at the root of sharp fluctuations in asset prices (Borio, Kennedy and Prowse, 1994). Strong "risk appetite" leading to investors' excessive optimism can create speculative bubbles on financial prices, building up vulnerabilities. Then a sudden reversal in risk aversion may trigger sharp falls in asset prices and prompt a financial crisis. One problem in assessing the different periods, "risk appetite" or risk aversion, is clearly distinguishing the risk perceived by agents from risk aversion itself.

Theoretically, risk aversion can be precisely defined within the framework of asset pricing models (Campbell, Lo and MacKinlay, 1997, Cochrane, 2001). In this context, a risk premium can be decomposed into a "price of risk", which is common to all assets, and a "quantity of risk" which is specific to each asset. Risk aversion can be considered as the "price of risk" obtained in this way. Other authors refer to "risk appetite", which is just the same "price of risk" with a negative sign (Kumar and Persaud, 2002, Gai and Vause, 2006).

Empirically, several methods have been developed in order to assess risk aversion. However, they yield indicators, which often show differing developments. The aim of the paper is to assess their respective relevance and their ability to predict crises.

Here we consider the most well-known ones: the GRAI type indicators, introduced by Kumar and Persaud (2002), based on the correlation between volatilities and changes in asset prices; indicators using a principal components analysis (PCA) on risk premia, as constructed by Sløk and Kennedy (2004); the VIX, using implicit volatility of option prices, created by the Chicago Board Options Exchange (CBOE, 2004); the LCVI, a synthetic indicator constructed by J.P. Morgan (Prat-Gay and McCormick, 1999, and Kantor and Caglayan, 2002); the ICI, used by State Street and based on the movements in investors' portfolios (Froot and O'Connell, 2003). We calculate the two first categories: the GRAI and a PCA indicator with empirical data on financial prices; we use the original series provided by their authors for the VIX, LCVI and ICI.

[1] Banque de France, DGO, DCSF, 31 rue Croix des Petits Champs, 75001 Paris – email : virginie.coudert@banque-France.fr , CEPN, université Paris 13, CEPII, 9 rue Georges Pitard, 75015 Paris.

[2] Banque de France, 31 rue des Petits Champs, 75001 Paris, CERAG, université Grenoble 2.

We then test these indicators ability to forecast currency and stock market crises. Much work has been done to attempt to construct "leading indicators" of crises, since the Mexican crisis in 1995 (Kaminsky, Lizondo and Reinhart, 1997, Berg and Patillo, 1999, Bussière and Fratzscher, 2006). The idea underlying this research has been to identify economic variables that behave in a particular way prior to periods of crisis. Their aim is to assess probabilities of crisis at a specific horizon (generally one or two years), taking account of the information available on the economic variables. Most of them use logit models that link a qualitative endogenous variable (equal to 1 for crises and 0 for quiet periods) to a set of quantitative exogenous variables (Frankel and Rose, 1996, Sachs, Tornell and Velasco, 1996, Radelet and Sachs, 1996). These models are estimated for a large number of countries and periods. We use the same method here, adding risk aversion indicators to the usual variables.

Section 2 theoretically states the risk aversion concept which will be used in the framework of standard asset pricing models (CCAPM and CAPM). Section 3 describes the empirical methods for constructing the risk aversion indicators. Section 4 gives the definition of crises for foreign exchange and stock markets; it also presents the different logit and multilogit models used for forecasting. We successively use these models with control variables and/or with each risk aversion indicator. Section 5 gives the estimation results and in-sample simulations for currency crises; section 6 for stock market crises and reversals. Section 7 concludes.

2. THEORETICAL FRAMEWORK

2.1 Risk aversion in the CCAPM

The CCAPM allows to link asset prices to the consumer's utility function. To keep it simple, we assume that there is a single risky asset, that the agent can buy and sell freely, two periods, *t* and *t*+1, constant consumer prices and a utility function that is separable over time. The agent's non-financial income in period *t*+1 is a stochastic variable depending on the state of the world in *t*+1. The agent maximises his expected utility by choosing an optimal quantity of asset to buy in the first period, as in the following programme.

$$\begin{cases} \max\limits_{\{\xi\}} u(c_t) + E_t\left[\delta u(c_{t+1})\right] \\ c_t = y_t - p_t \xi \\ c_{t+1} = y_{t+1} + x_{t+1}\xi \end{cases} \tag{1}$$

We denote consumption in *t* as c_t, non-financial revenue as y_t, the price of the asset as p_t, gross income from the asset x_{t+1}, and the quantity of asset bought in *t* as ξ. δ is the intertemporal discount factor, which captures the consumer's preference for present.

The price of the asset p_t is deduced from the first order condition:

$$p_t = E_t\left[\delta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1}\right] \tag{2}$$

The asset price expressed in equation (2) can be interpreted as the expected income x_{t+1}, discounted by a discount factor, denoted m_{t+1} and referred to as the "stochastic discount factor" (SDF, thereafter):

$$p_t = E_t\left(m_{t+1} x_{t+1}\right) \tag{3}$$

with

$$m_{t+1} = \delta\left[u'(c_{t+1})/u'(c_t)\right] \tag{4}$$

To express the risk premia, we use the gross return on the asset, dividing income x_{t+1} by the price p_t (i.e. $R_{t+1} = x_{t+1}/p_t$)[1]:

$$1 = E\left(m_{t+1} R_{t+1}\right) \tag{5}$$

By definition, the income from a risk-free asset does not vary with states of the world, which amounts to saying that the risk-free rate in t+1, denoted R^f_{t+1}, is known in advance:

$$R^f_{t+1} = \frac{1}{E\left(m_{t+1}\right)} \tag{6}$$

By definition, the risk premium equals the difference $E\left(R_{t+1}\right) - R^f_{t+1}$, i.e. the expected excess return on the risky asset compared to that on the risk-free asset.

Considering equations (5) and (6), we have:

$$E\left(R_{t+1}\right) - R^f_{t+1} = -\operatorname{cov}\left(m_{t+1}, R_{t+}\right) R^f_{t+1} \tag{7}$$

The risk premium therefore equals minus the covariance of the return on the risky asset with the SDF multiplied by the risk-free rate. It can be decomposed as follows:

$$E\left(R_{t+1}\right) - R^f_{t+1} = \left(-\frac{\operatorname{cov}\left(R_{t+1}, m_{t+1}\right)}{\operatorname{var}\left(m_{t+1}\right)}\right)\left(\frac{\operatorname{var}\left(m_{t+1}\right)}{E\left(m_{t+1}\right)}\right) \tag{8}$$

Generally speaking, assuming there are several assets subscripted from i = 1 to n:

$$E\left(R^i_{t+1}\right) - R^f_{t+1} = \left(-\frac{\operatorname{cov}\left(R^i_{t+1}, m_{t+1}\right)}{\operatorname{var}\left(m_{t+1}\right)}\right)\left(\frac{\operatorname{var}\left(m_{t+1}\right)}{E\left(m_{t+1}\right)}\right) \tag{9}$$

[1] To lighten the notation, from now on, we suppress the subscripts on E_t, as well as on the variance and covariance, for they are all calculated in time t.

which can be written in the form:

$$E\left(R_{t+1}^{i}\right)-R_{t+1}^{f}=\beta_{i,m}\lambda_{m} \tag{10}$$

with

$$\beta_{i,m}=-\frac{\operatorname{cov}\left(R_{t+1}^{i},m_{t+1}\right)}{\operatorname{var}\left(m_{t+1}\right)} \tag{11}$$

and

$$\lambda_{m}=\frac{\operatorname{var}\left(m_{t+1}\right)}{E\left(m_{t+1}\right)} \tag{12}$$

We can consider that λ_m is the price of risk, which is common to all assets, and that $\beta_{i,m}$ is the specific quantity of risk associated with each asset.

Often, the price of risk λ_m is regarded as corresponding to risk aversion. We do the same in this paper. However, to avoid any confusion, it should be distinguished from the parameter of risk aversion in the consumer's utility function. For example, using the conventional power utility function $u(c_t)=\frac{1}{1-\gamma}c_t^{1-\gamma}$, where γ is the coefficient of relative risk aversion, the SDF is written:

$$m_{t+1}=\delta\left(c_{t+1}/c_{t}\right)^{-\gamma}. \tag{13}$$

The expected return and price of risk depend on the rate of growth in consumption, denoted Δc :

$$\begin{aligned}E\left(R_{t+1}^{i}\right)&=R_{t+1}^{f}+\beta_{i,\Delta c}\lambda_{\Delta c}\\ \lambda_{\Delta c}&=\gamma\operatorname{var}(\Delta c)\end{aligned} \tag{14}$$

2.2 Consistency with the CAPM

The CCAPM model may be regarded as being a general representation from which the other models currently used to determine asset prices can be deduced. The CAPM of Sharpe (1964) and Lintner (1965a, 1965b) may be considered a particular case of the CCAPM. We therefore express the SDF depending on the return, denoted R_{t+1}^{W}, on the "wealth portfolio" held by the consumer. This return R^W thus serves to approximate the marginal utility of consumption:

$$m_{t+1}=a-bR_{t+1}^{W} \tag{15}$$

a and b are parameters > 0.[2]

R^W is proxied by the return on a broad portfolio of stocks regarded as "the market portfolio". The return on the market portfolio, denoted R^m, equals the average return on all of the assets indexed by i = 1 to n weighted by their share α_i, so that:

$$R_{t+1}^m = \sum_i \alpha_i R_{t+1}^i \tag{16}$$

This assumes that the consumer's wealth is invested across the whole of the market. If the return on the market portfolio is denoted R^m, the SDF will then be:

$$m_{t+1} = a - bR_{t+1}^m \tag{17}$$

Using equations (7) and (17) and assuming again that there are several assets, indexed by $i = 1$ to n, then:

$$E\left(R_{t+1}^i\right) = R_{t+1}^f - R_{t+1}^f \operatorname{cov}\left(R_{t+1}^i, a - bR_{t+1}^m\right) = R_{t+1}^f + R_{t+1}^f b \operatorname{cov}\left(R_{t+1}^i, R_{t+1}^m\right) \tag{18}$$

The expression of the risk premium is obtained by dividing and multiplying the right side of equation (18) by $\operatorname{var}\left(R_{t+1}^m\right)$:

$$E\left(R_{t+1}^i\right) = R_{t+1}^f + R_{t+1}^f b \operatorname{var}\left(R_{t+1}^m\right)\left(\frac{\operatorname{cov}\left(R_{t+1}^i, R_{t+1}^m\right)}{\operatorname{var}\left(R_{t+1}^m\right)}\right) \tag{19}$$

Identifying to equation (6), we can write (19) in the following form, which is consistent with the CCAPM:

$$E\left(R_{t+1}^i\right) = R_{t+1}^f + \beta_{i,m}\lambda_m \tag{20}$$

with

$$\beta_{i,m} = \frac{\operatorname{cov}\left(R_{t+1}^i, R_{t+1}^m\right)}{\operatorname{var}\left(R_{t+1}^m\right)} \tag{21}$$

and

$$\lambda_m = b\,\frac{\operatorname{var}\left(R_{t+1}^m\right)}{E\left(R_{t+1}^m\right)} \tag{22}$$

[2] The theoretical values of these parameters are obtained by setting: $1 = E_t(m_{t+1} R^W_{t+1})$ et $1 = E_t(m_{t+1})R^f_{t+1}$.

The market return plays a similar role to that of changes in consumption in the previous model.

2.3 Consistency with factor models

The Arbitrage Pricing Theory (APT) (Ross, 1976), based on the lack of arbitrage opportunities, relies on the assumption that yields on different securities depend on one or more common factors which are not directly observable. APT specifies neither their number nor their nature. In the framework of the CAPM, the only factor to consider is the market return. In other models, several factors are retained. For instance, Fama and French (1996) show that a three-factor model may explain the change in excess return of US stocks portfolios. The SDF is expressed according to a number of factors *f*, which may be different from consumption or market returns.

$$m_{t+1} = f_{t+1}'b \tag{23}$$

As the factors *f* are not directly observable, a factor analysis method, such as a Principal Component Analysis (PCA), is needed to estimate them (see Cochrane, 2001, p. 175).

3. THE RISK AVERSION INDICATORS

3.1 Indicators of the GRAI type

An increase in risk aversion should lead to a rise in risk premia across all markets, but the rise should be greater on the riskiest markets. This is the idea on which the Global Risk Aversion Index (GRAI) is based, devised by Persaud (1996): changes in risk aversion may therefore be represented by the correlation across different assets between price variations and their volatility.

The framework is given by a CAPM model of the type that we can express as in (20), (21) and (22). If we add an assumption of independent returns on different markets, the risk premium on each security *i* no longer depends on the covariance with other premia, but only on the security's variance (denoted σ_i^2).

$$E\left(R_{t+1}^i\right) - R_{t+1}^f = \lambda \frac{\operatorname{cov}\left(R_{t+1}^i, \alpha_i R_{t+1}^i\right)}{\operatorname{var}\left(R_{t+1}^m\right)} = \lambda \frac{\alpha_i \sigma_i^2}{\sigma_m^2} \tag{24}$$

By deriving formula (24) in relation to λ, we obtain the change in the expected risk premium when risk aversion increases:

$$\frac{\partial\left[E\left(R_{t+1}^i\right) - R_{t+1}^f\right]}{\partial \lambda} = \frac{\alpha_i \sigma_i^2}{\sigma_m^2} \tag{25}$$

Thus, an increase in risk aversion results in an increase in the expected risk premium of the asset *i* that is proportional to the volatility of asset *i*'s return, according to equation (25).

By deriving formula (24) in relation to σ_i^2, we obtain the change in the risk premium across the different assets 1,…, *n* when the asset's volatility, i.e. the risk associated with *i*, increases:

$$\frac{\partial\left[E\left(R_{t+1}^i\right)-R_{t+1}^f\right]}{\partial\sigma_i^2}=\frac{\alpha_i\lambda}{\sigma_m^2} \tag{26}$$

Equation (26) shows that an increase in asset *i*'s volatility brings about an increase in the risk premium of *i* that is proportional to the risk aversion, but does not depend on *i*'s volatility.

The GRAI indicators calculated use variations in prices rather than in expected excess returns, which explains the change in sign in the correlation.

The expected return equals the anticipated change in price:

$$E\left(R_{t+1}^i\right)=E(P_{t+1}^i)-P_t \tag{27}$$

By assuming that $E\left(P_{t+1}^i\right)$ is constant and using (27) and (24), we obtain:

$$\frac{\partial\left[P_t\right]}{\partial\lambda}=-\frac{\alpha_i\sigma_i^2}{\sigma_m^2} \tag{28}$$

The GRAI is therefore calculated as a correlation with a negative sign between price changes of the different assets and their volatility. By construction, the GRAI does not measure levels of risk aversion but rather changes in it. Spearman's correlation is often used, which is a correlation between ranks of variables. Instead of a correlation, a regression coefficient between price variations and volatilities may also be used (which is also given a negative sign). The indicator is then called the Risk Aversion Index (RAI), as proposed by Wilmot, Mielczarski and Sweeney, (2004).

In order to be entirely rigorous, confidence intervals need to be constructed around the estimated values. When this is done, GRAI indicators are often found to be in a non-significant area (more than half of the values in Kumar and Persaud's study). However, it must be admitted that these confidence intervals are not calculated for other empirical risk aversion indicators. Kumar and Persaud (2002) applied this approach to ex post excess returns on foreign exchange markets, Baek *et al*. (2005) on developed and emerging stock markets. Several financial institutions and private banks, such as the IMF and J.P. Morgan, subsequently constructed their own GRAI. Other like Crédit Suisse First Boston (Wilmot, Mielczarski and Sweeney, 2004) and the Deutsche Bundesbank (2005) have constructed RAIs.

From a theoretical standpoint, the construction is based on simplifying assumptions that are probably not borne out in reality, notably, the independence of excess returns and the independence between expected future prices and variations in risk aversion (Misina, 2003, 2006). From an empirical point of view, the GRAI and RAI also display some limitations. The measurements show that these indicators are very volatile. This seems counter-intuitive, as a good indicator should be stable during quiet periods. Moreover, changes in the indicator over time differ quite markedly depending on the period chosen for the calculations of volatility of returns as well as on the market concerned.

We calculate a GRAI and a RAI for the foreign exchange and stock markets using monthly data. Volatility is calculated over the two previous years. For the currency GRAI, the sample comprises 12 to 15 currencies quoted against the US dollar depending on the periods for which data are available; excess returns are equal to the spread between the 3-month forward rate and the actual spot rate three months later. For the stock market GRAI, the sample is made up of the main stock market indices of 27 developed and emerging economies.

3.2 A PCA indicator

As shown in section 2.3, in the framework of a factor model, a PCA should be applied to risk premia in order to identify common factors in their variations. The first common factor can generally be interpreted as the price of risk, if certain conditions are met, notably that it increases with each risk premium. In fact, this indicator is constructed exactly like a weighted average of risk premia, the weighting being given by the PCA.

PCA allows to extract from a set of n quantitative variables correlated among one another a list of p new variables called "factors" $f_1,\ldots,f_p$ ($p \leq n$) that are uncorrelated among one another. The common factors are constructed as linear combinations of n initial variables. In order to condense the information, only the k first factors are considered, as they explain, by construction, the bulk of total variance. The proportion of total variance accounted for by these k first factors constitutes an overall measure of the quality of the PCA. Choosing how many factors to use is difficult. Two criteria are often used to make this choice: the Joliffe criterion – which consists in cutting off once the percentage of explained variance reaches a certain threshold (for example 80%) – and the Kaiser criterion, which only keeps eigenvalues greater than one if the correlation matrix is worked on.

This PCA approach is used by Sløk and Kennedy (2004) on stock and bond markets in developed and emerging market countries. According to them, the variance-explained weighted average of the first two common factors is strongly correlated with the OECD's leading indicator of industrial production and a measure of global liquidity. In this case, therefore, PCA captures the impact of the risk of the overall macroeconomic environment and liquidity risk on changes in risk premia. McGuire and Schrijvers (2003) studied – also using PCA – common developments in risk premia in 15 emerging market countries. The first factor, which explains the bulk of the common variation, is interpreted as representing the investor risk aversion. The Deutsche Bundesbank (2004) calculates a risk aversion indicator by means of PCA using risk premia on investment and speculative grade corporate bonds in developed countries and sovereign risk premia for some Asian and Latin American countries.

Here we calculate a PCA indicator on risk premia. The risk premia used have been chosen so as to be representative of the changes observed across the fixed income market as a whole. These are, on the one hand, option adjusted spreads (OAS) on corporate bonds and swap spreads for the major developed markets; and, on the other, the EMBI Global sovereign spread and a corporate spread for emerging market economies.[3] Details of these series are given in Appendix 1. The estimation period is from December 1998, when the indices used for emerging market countries were introduced, to December 2005. The method used here is PCA carried out using a set of standardised risk premia.

The results show that the first factor explains 68% of the common variation of risk premia. The correlation of each of the risk premia with this first factor is positive. In addition, all of the original risk premia are well represented in this first factor, the weightings being of comparable order of magnitude (Table 1); there is therefore no problem of over- or under-representation of certain series. For these reasons, we can consider that this first common factor gives a good representation of risk aversion.

The second factor explains 19% of the common variation of risk premia. We analyse it since it satisfies the Joliffe criterion, at the 80% threshold, and the Kaiser criterion. This second factor is negatively correlated with a measure of global liquidity. This is approximated here by the inverse of average short-term rates of the four largest economies (United States, euro area, United Kingdom and Japan), weighted by GDP (ρ = -0,69). We also note a high positive correlation between the second factor and swap spreads, which are often regarded as being strongly influenced by global liquidity developments.

3.3 Simple and aggregated indicators: the VIX and the LCVI

Some analysts use raw series to estimate changes in investors' perception of risk. For instance, the price of gold is sometimes used on the basis that, during periods of uncertainty, investors reallocate their wealth to assets traditionally perceived as safe, such as gold. The same is true of the Swiss franc exchange rate.

The implied volatility of options is also used to provide an indication of the amounts an investor is prepared to pay to protect himself from the risk of price fluctuations. The Volatility Index (VIX), used in the following sections, equals the implied volatility on the S&P 500. It is regarded by many market analysts as a direct gauge of fear (CBOE, 2004).

Several indicators have been created by aggregating elementary series. These measures are relatively simple to put in place and can be easily interpreted. In most cases, they are weighted averages of a number of variables. The best-known indicators of this type are J.P. Morgan's Liquidity, Credit and Volatility Index or LCVI (Prat-Gay and McCormick, 1999, and Kantor and Caglayan, 2002), UBS's Risk Index (Germanier, 2003), Merrill Lynch's Financial Stress Index (Rosenberg, 2003) and the Risk Perception Indicator of the *Caisse des Dépôts et Consignations* (Tampereau and Teiletche, 2001).

---

[3] Risk premia on stock markets are not used on account of the great disparity in results obtained using the principal methods, which are mainly based on the Gordon-Shapiro model but with different underlying assumptions.

We select the LCVI, often regarded as being a satisfactory measure of risk aversion. Dungey *et al.* (2003), for example, use it to study changes in risk aversion during the financial crises in emerging markets. The LCVI aggregates three types of information: first, two series capturing liquidity developments (yield spreads between a benchmark and little-traded US Treasury bills and spreads on US swaps); second, two risk premia indicators (yield spreads on speculative grade corporate bonds and the EMBI); and third, three measures regarded in this approach as representative of market volatility (the VIX, volatility on foreign exchange markets and the Global Risk Aversion Index – GRAI).

These aggregate indicators may seem limited in their power to explain risk perception, as the underlying elementary variables are influenced by many factors other than investors' propensity to take risks. This is not offset by aggregating them, which consists, more or less, in calculating an arithmetical average, with an arbitrary weighting of the different series.

3.4 Other measures: the ICI

We also select the State Street's Investor Confidence Index (ICI) which is based on a measure in volume terms rather than prices (Froot and O'Connell, 2003). This index can be regarded as a GRAI calculated in terms of quantities. A rise in it corresponds to an increase in risky assets in the portfolio of a range of investors. It thus points to a trend of growing risk appetite, and a fall signals the reverse. In order to compare it directly with other risk aversion indicators, we give it a negative sign. The index is calculated every month using State Street's proprietary database on the portfolios of institutional investors.

Option prices are also used to extract information on risk aversion. Indicators based on option prices are obtained by comparing risk-neutral probabilities, calculated on options prices, with investors' subjective probabilities (Tarashev *et al.*, 2003, Scheicher, 2003, Bliss and Panigirtzoglou, 2004, for a survey, see Gai and Vause, 2004). We have not used this type of indicator here as it is tricky to estimate empirically subjective probabilities using historical data. We have not used either in our comparison indicators based on the optimisation under constraint of a consumption model, of which the Goldman Sachs indicator is an example (Ades and Fuentes, 2003). Indeed, many studies have shown that the CCAPM underperform models that use market data, such as the CAPM, and conclude to its low explicative power (Mankiw and Shapiro, 1986, Cochrane, 1996, Hansen and Singleton, 1982, 1983 and Wheatley, 1988). However, the CCAPM theoretical model is still not discredited since these poor empirical findings may come from specifications on the utility function or on the parameters (Campbell and Cochrane, 2000).

3.5 Comparison of the indicators

The different indicators react more or less to periods of crisis (see Appendix 2, these periods are identified by vertical columns). Prior to the Asian crisis in 1997 and the Russian crisis in the summer of 1998, the VIX and LCVI show a rise in risk aversion. Prior to the Asian crisis in 1997 and the Russian crisis in the summer of 1998, the VIX and LCVI show

a rise in risk aversion.[4] However, the GRAI and RAI do not display any very clear trend. During the stock market crisis in the early 2000s, several indicators signal an increase in risk aversion: the PCA, the GRAI and the RAI (which are positive as they point to a rise in risk aversion). The VIX, LCVI and ICI do not show any very clear trend. The terrorist attacks of 11 September 2001 coincide with a peak of risk aversion in the VIX, the LCVI and the PCA. The other indicators do not record any particular change at this time.

One reassuring point to be underlined, however, is that these indicators are positively correlated between one another, even if the variations in them differ. The cross-correlations of these indicators show that 21 out of 28 of these correlations are positive (Table 2). Of the seven remaining, only three are significantly different from zero.

4. TESTING THE PREDICTIVE POWER OF THE INDICATORS

We attempt to determine whether the risk aversion indicators described above can serve as leading indicators of crises, or whether they can help to improve forecasts using existing models. All along, we assume that a "good" risk aversion indicator should increase before a currency or stock market crisis.

We carry out two estimates: on the foreign exchange market and on the stock market. Theoretically, investor risk aversion is the same on all markets, as a rational investor maximises his expected gains by making investment choices across all types of assets. We will therefore use the same risk aversion indicators, except for the GRAI where we have two distinct indicators. The sample of panel data includes monthly data for the period from July 1995 to September 2005 for 20 emerging countries for currency crises and 27 countries for stock market crises. The countries and exact sources of the series are given in Appendix 1.

4.1 Definition of currency crises

In order to construct leading indicators of crises, an essential first step is to identify the crisis periods that occurred in the sample under review. Crisis periods are identified by so-called "simultaneous" indicators, which will be used to construct the model's dependent variable. The usual method consists in first of all constructing a "pressure" indicator on the foreign exchange market (for example, Sachs, Tornell and Velasco, 1996, Kaminsky, Lizondo and Reinhart, 1997, Corsetti, Pesenti and Roubini, 1998, Burkart and Coudert, 2002, Bussière and Fratzscher, 2006).

For each country *i*, the pressure indicator, denoted $C'_{i,t}$, equals a weighted average of the currency's depreciation, $e_{i,t}$, and relative losses in international reserves, $r_{i,t}$.

[4] In the case of the LCVI, only the Russian crisis is concerned, as the series is only available from the end of 1997.

$$C'_{i,t} = \alpha_{i,t} e_{i,t} + (1-\alpha_{i,t}) r_{i,t} \tag{29}$$

$$\alpha_{i,t} = 1/\mathrm{var}_t(e_{i,t}) \; / \; [1/\mathrm{var}_t(e_{i,t}) + 1/\mathrm{var}_t(r_{i,t})]$$

The weighting used between the two series is inversely proportional to their conditional variance. The reference currency to measure depreciation is the dollar for all the currencies of Latin America and Asia, since they are regarded as being more or less part of a "dollar area". In the case of European currencies, we have used the euro (and the Deutsche Mark before 1999) except when the currency was pegged to another currency. For example, when currencies were pegged to a basket, it is the change relative to this basket that is considered (for example, Hungary and Poland from July 1995 to December 1999). Countries that have had periods of hyperinflation (defined here by inflation higher than 150% in the six preceding months) are given particular treatment (in our sample, Bulgaria and Romania). In this case, we split the sample into two sub-samples: a sub-period of normal inflation and another of hyperinflation, as the measurement of averages and standard deviations is different for these two types of period.

When the pressure indicator goes above a certain threshold, it is deemed that there is a currency crisis. The threshold used is generally two or three standard deviations above the mean. The greater the number of standard deviations, the smaller the number of identified crises. Here we set the number of standard deviations to 3. This threshold allows to detect all the known crises in the sample (the Asian countries in the second half of 1997 or in Brazil in January 1999 and Argentina in January 2002). The currency crisis indicator $C_{i,t}$ is then defined as

$$\begin{aligned} C_{i,t}^{Currency} &= 1 \quad \text{if} \quad C'_{i,t} >_t \overline{C'_{i,t}} + 3\sigma_{i,t} \\ C_{i,t}^{Currency} &= 0, \quad \text{otherwise.} \end{aligned} \tag{30}$$

The average $\overline{C'_{i,t}}$ and standard deviation $\sigma_{i,t}$ are first calculated on data from August 1993 to December 1997, then conditionally by gradually adding one month to the sample. Here again in the case of hyperinflation countries, we split the sample into two sub-samples.

We add an extra criterion to avoid counting the same crisis several times: if a crisis is detected within a 12-month period following another crisis, it is automatically cancelled out. In total, 18 crises are detected, that is, an average 0.9 crisis per country over the period (Appendix 3.1).

4.2 Definition of stock market crises

There are fewer studies that address stock market crises. Nonetheless, it seems reasonable to define a stock market crisis as a sharp and rapid drop in share prices or in an index.[5] Two methods are used. Mishkin and White (2002) identify crises as falls in the price of a security or an index below a certain threshold (set arbitrarily at 20%) over a chosen time period (which may be a week, a month, a year, etc.)

Patel and Sarkar's approach (1998) consists in calculating an indicator, the *CMAX*, which detects extreme price levels over a given period (set to 24 months). This involves dividing the current price by the maximum price over the previous 2-year period. If $P_{i,t}$ is the stock price at time t and i, the country, then:

$$CMAX_{i,t} = \frac{P_{i,t}}{\max\left(P_{i,t}, \ldots, P_{i,t-24}\right)} \tag{31}$$

This indicator equals 1 when $P_{i,t} = \max\left(P_{i,t}, \ldots, P_{i,t-24}\right)$.This is the case when that is a monotonous upward trend during the preceding 2 years. The more prices fall, the closer $CMAX_{i,t}$ gets to 0. Here again, to define crises, a threshold is used to identify periods when $CMAX_{i,t}$ is abnormally low. The threshold used is generally equal to the mean less two or three standard deviations.

Over our sample, by using a threshold of two standard deviations below the mean, we identify crises that correspond to recognised events over the period (see Appendix 3.1). The stock market crisis indicator $C_{i,t}^{Stock}$ is defined as following:

$$\begin{aligned} &C_{i,t}^{Stock} = 1 \quad \text{if} \quad CMAX_{i,t} < \overline{CMAX}_{i,t} - 2\sigma_{i,t} \\ &C_{i,t}^{Stock} = 0, \quad \text{otherwise.} \end{aligned} \tag{32}$$

In order to have a sufficiently large sample, the mean $\overline{CMAX}_{i,t}$ and standard deviation $\sigma_{i,t}$ are first calculated over 10 years from March 1995 to March 2005 and then conditionally by gradually adding one month at a time to the sample. As with currency crises, if a crisis is detected within a 12-month period following another crisis, it is automatically cancelled out. There are 30 crises in the sample, i.e. an average of 1.1 crises per country. They all occur during the stock market fall in the early 2000s (see Appendix 2).

[5] An alternative approach consists in seeking to detect the bursting of speculative bubbles, defined as the emergence of a substantial and lasting deviation of a share price or index from its fundamental price, followed by an adjustment period then a return to the fundamental equilibrium. The difficulty in applying/implementing this method lies in the practical determination of the fundamental value as well as the econometric identification of these bubbles (Boucher, 2004).

Given the indicator's construction, the fall in share prices is already well under way when it signals a crisis. It is not, therefore, the turning point that is identified, but rather the point at which there has already been an abnormal drop in prices. On the other hand, the advantage of this indicator is that it only identifies confirmed crises that wipe out a substantial share of the gains made over the two previous years.

4.3 The dependent variable

Using the crises defined above, we construct an indicator denoted $I_{i,t}$ composed solely of 0s and 1s. It equals 1 for the 12 months preceding crises and the crisis itself, and 0 in the quiet periods. The 11 months following the crisis are excluded from the sample as the post-crisis period is irrelevant for the estimates and may even distort estimates if it is aggregated with quiet periods:

$$\begin{aligned} &I_{i,t} = 1 \quad \text{if} \quad \exists k \in \{0,\ldots,12\} \quad \text{such as} \quad C_{i,t+k} = 1 \\ &I_{i,t} = n.a. \quad \text{if} \quad \exists k \in \{1,\ldots,11\} \quad \text{such as} \quad C_{i,t-k} = 1 \\ &I_{i,t} = 0, \quad \text{otherwise.} \end{aligned} \tag{33}$$

The number of 1s in this indicator is therefore roughly 12 times bigger than the number of crises actually spotted. This is the indicator used as a dependent variable in the regressions that follow. In seeking to estimate the probability that the variable $I_{i,t}$ is equal to 1, we estimate the probability of a crisis within a one-year horizon. For the sake of brevity, we will refer to this indicator $I_{i,t}$ as a "crisis indicator", using a misnomer.

For multilogit models, a second variable $J_{i,t}$ is constructed in order to discriminate the periods just following the crises. It is equal to the previous one, except that it is set to 2 during the 11 periods following the crises.

$$\begin{aligned} &J_{i,t} = 2 \quad \text{if} \quad \exists k \in \{1,\ldots,11\} \quad \text{such as} \quad C_{i,t-k} = 1 \\ &J_{i,t} = I_{i,t}, \quad \text{otherwise.} \end{aligned} \tag{34}$$

4.4 The models used

We carry out three types of estimate in turn. First, we estimate a base model, denoted Model (1), with the explanatory variables that are generally used to predict crises. This model is as follows:

$$\Pr\left(I_{i,t} = 1\right) = f\left(\alpha_0 + \sum_{k=1}^{n} \alpha_k X_{i,t}^k\right) \tag{35}$$

where $I_{i,t}$ is the crisis indicator variable described above, $X_{i,t}^k$ the explanatory variables for crises, and f a logistical function of the type: $f(z) = \frac{e^z}{1+e^z}$.

Secondly, Model (2) estimates the same equation with the control variables $X_{i,t}^{k}$ by adding a risk aversion indicator λ_t among the explanatory variables:

$$\Pr\left(I_{i,t}=1\right)=f\left(\alpha_0+\sum_{k=1}^{n}\alpha_k X_{i,t}^{k}+\alpha_{n+1}\lambda_t\right) \tag{36}$$

We try out, in turn, the VIX, the LCVI, the PCA, the GRAI, the RAI and the ICI as the risk aversion indicator λ_t.

Thirdly, Model (3) estimates the same equation with the risk aversion indicator as the only explanatory:

$$\Pr\left(I_{i,t}=1\right)=f\left(\alpha_0+\alpha_{n+1}\lambda_t\right) \tag{37}$$

The aim is to compare the results obtained with these three similar types of model. To do this, the estimation sample must be identical. However, as some of our indicators (LCVI, PCA and ICI) start later – in December 1998 – we estimate Models (2) and (3), which use these variables over this truncated period. In order to be able to compare them with the base models, we re-estimate this model over the same period.

In the same way, we estimate successively three multilogit models which include post-crisis periods by using $J_{i,t}$ as the crisis indicator variable.[6] We want to see if this method improves the quality of the models as well as their predictive power.

For currency crises, most studies use the same explanatory variables in their model (for an exhaustive list, see Berg and Patillo, 1999). Here we tried out a number of variables and used those that are significant for our sample. These are the real exchange rate (against the dollar for Asian and Latin American countries and against the euro for European countries, quoted directly, with an increase corresponding to a depreciation of the emerging economy's currency); official international reserves as a ratio of broad money, in year-on-year terms; and the interest rate on the money market taken in real terms.

For the stock market, the explanatory variables used, among those proposed by Boucher (2004), are the following: the price earnings ratio (PER) in level terms, the year-on-year change in stock prices, and real interest rates. All of these explanatory variables have been standardised for each country in order to obtain homogenous data for all countries.

4.5 Assessing the predictive power

The fitted values of the regression results give the estimated probabilities of a crisis. In order to obtain genuine crisis "predictions", we should estimate the models over a given period, then simulate them out-of-sample, that is, over a period subsequent to the estimates.

[6] For a detailed discussion of multilogit models, see Pindyck and Rubinfeld (1998), section 11.2.

Here we calculate these fitted values in the sample, because the time span of our data is too limited to shorten the estimation period. In addition, it would have been difficult to use this as a basis to assess the model's power to predict crises, as the sample includes very few crises at the end of the period.

In order to obtain crisis predictions, a probability threshold needs to be set, above which it is decided that a crisis is predicted by the model. Here we have used 20%, to present the results. This level is comparable to those chosen in similar studies (see, for example, Berg and Patillo, who review existing models in order to compare them and set thresholds at 25% and 50%).

We assess the predictive power of the models by calculating two ratios: the percentage of correctly predicted crises, which equals the number of crises correctly predicted divided by the total number of crises; the ratio of "false alarms", which equals the number of crises wrongly predicted divided by the number of crises predicted.

5. FORECASTING OF CURRENCY CRISES

5.1 Significance of the control variables and the risk aversion indicators

In Models (1) and (2), the explanatory variables of currency crises have the expected signs (Table 3). Appreciation of the real exchange rate and a fall in international reserves relative to broad money are supposed to increase the risk of crisis, which corresponds to the negative signs found. The sign is positive on the real interest rate, an increase in which may signal a central bank's difficulty in maintaining the currency's parity. These three variables are significantly different from zero at the 99% level over the two estimation periods. The estimates are markedly more fragile for the shorter period as the number of crises is smaller, falling from 18 to 7 (for example, the Asian crises in 1997 disappear from the sample).

In Models (2) and (3), the risk aversion variables have the expected positive sign, which means that a rise in them contributes to increasing the probability of a crisis. The only exceptions are the ICI, which is found negative, and the LCVI, not significantly different from zero (Table 3 and 4).

The multilogit estimates confirm the results for the pre-crisis periods. They also improve the regression quality (McFadden pseudo R^2 and likelihood). In the post-crisis periods, most significant risk aversion indicators have a positive coefficient (except the PCA in Model (2)) (Tables 5 and 6). The positive sign found could be interpreted by the fact that investors remain timid during a certain period of time after the crises. On the contrary, if there was an instant renewal of optimism after the crisis, the sign would have been negative.

5.2 Predictive power for currency crises

Sixty-one percent of crises are correctly predicted by the base Model, when estimated on the longer period (July 1995 to September 2005); the ratio of false alarms is 59% (Table 3).

Graphs of estimated probabilities of crises are given for four countries in Appendix 3.2. As previously noticed, when estimation is made on the reduced period (starting in December 1998), results are less reliable, which implies that the percentage of correctly predicted crises falls (to 24%).

Introducing a risk aversion indicator only slightly improves the model's forecasts. The best performing risk aversion indicators – the GRAI and the PCA – only add 2% to the percentage of correctly predicted crises compared to the base model, while slightly reducing the ratio of false alarms. The RAI and the VIX only add 1%, the LCVI 0%. When taken alone in model (3), the predictive capacity of all risk aversion indicators is null (Table 4). Results are not very different with multilogit models (Table 5 and 6). Here, the indicators PCA and LCVI improve the predictive power of the model by 4% on the reduced period.

6. FORECASTING OF STOCK MARKET CRISES

6.1 Significance of the control variables and the risk aversion indicators

Unlike in the previous case, shortening the estimation period does not reduce the quality of the estimates. Indeed, the number of crises in the sample is not affected if we start our estimates in December 1998, given that all of the stock market crises took place in the early 2000s. As a result, here we only present the results for the shorter period, which makes it possible to compare the accuracy of the different indicators directly.

All of the explanatory variables introduced into the base model of stock market crises are significant (Table 7). The sign is positive for the PER, an increase in which may indicate an overvaluation of stock prices. It is negative for returns, which already tend to decline at the onset of the crisis, as well as for real interest rates.

When they are introduced into the regressions on stock market crises, the risk aversion indicators are significant and positive both with the other explanatory variables (Table 7) or when taken alone (Table 8). Here again, the only exception is the ICI.

In the multilogit estimates, the post-crisis periods are mainly associated with negative coefficients for risk aversion indicators, (Tables 9 and 10), which means that the risk aversion decreases just after the crisis.

6.2 Predictive power for stock market crises

The base model predicts 84% of stock market crises, with a false alarm ratio of 50%. Appendix 3.2 gives the results for 4 selected countries. Added into a regression with the control variables, the risk aversion indicators lightly increase these good results in terms of prediction (Table 7). One interesting result is that even when they are taken alone, all the risk aversion indicators obtain good results (with the exception of the LCVI). The PCA perform best, with 75% of crises correctly predicted and 62% of false alarms, then come the GRAI and the RAI (with 56% to 67% of crises correctly predicted and around 70% of false alarms) (Table 8). As for currency crises, multilogit models do not improve these forecasts (Tables 9 and 10).

How can the PCA's good performance be explained? As the PCA is a linear combination of the eight spreads on which it is calculated, we may wonder whether the estimates would be further improved by replacing this PCA indicator in regressions by the spreads themselves. The results show that the eight spreads give estimates that are more or less equivalent to those obtained with the PCA (Table 11): for example 88% of correctly predicted crises, versus 87% with the PCA in Model (2); 76% versus 75% in Model (3). Using a synthetic indicator such as the PCA is therefore preferable.

These good results in predicting stock market crises should be interpreted, recalling that it is not the turning point that is predicted by the model, but a point when the drop in stock prices is already such that the situation is "abnormal". Consequently, it is not surprising that risk aversion has already started to increase before the crisis thus defined breaks out.

6.3 Can stock market reversals be predicted?

By construction, the previous indicator detects stock market crisis once the prices have already strongly fallen down. So it detects crises when they are already well developed. It is also interesting to observe the behaviour of the risk aversion indicators around the reversal points, when the prices are the highest.

We detect stock market reversals using the stock market crises previously displayed. When a crisis is identified, we detect the reversal point as the maximum price over the two previous years:

$$R_{i,t} = 1 \quad \text{if} \begin{cases} \exists k \in \{0,\ldots,24\} \quad \text{such as} \quad C_{i,t+k} = 1 \\ \text{and} \\ P_{i,t} = \max\left(P_{i,t},\ldots,P_{i,t+24}\right) \end{cases} \tag{38}$$

As for previous crisis indicators, we construct the reversal indicator $I'_{i,t}$ that equals 1 during the reversal and the 12 preceding months; 0 during the quiet periods. The 11 months following the reversal are excluded from the sample. For multilogit models, the reversal indicator $J'_{i,t}$ equals $I'_{i,t}$ except for the post crises periods, for which it is set to 2.

All the dependent variables are significant in Model (1) (Table 12). The risk aversion indicators are significant and positive in Model (2) and (3), except the ICI (Tables 12 and 13). Therefore, risk aversion increases during the periods preceding the crises. This matches the investor's feeling of wariness regarding the carrying on with the market upward trend.

Here again, multilogit models improve the estimates. The behaviour of risk aversion indicators is homogenous during the post-crisis period: in Models (2) and (3), the indicators' coefficients are significant and positive, except the ICI (Tables 14 and 15). The positive sign means that risk aversion carries on increasing after the reversal. This is consistent with the fact that the crisis is not instantly cleared up, but span a certain amount of time.

Model (1) allows to predict 51% of the reversals, with a false alarms ratio of 65%. Some of the risk aversion indicators improve the forecasts, notably the PCA and the LCVI (70% and 66% of correctly predicted crises) (Table 12). When used alone, the best performances in reversals detection are also obtained by the PCA and the LCVI (35% and 46%). On the other hand, the VIX and the RAI's predictive power are null (Table 13). The false alarms ratio remains high for all the indicators (more than 70%). The multilogit models do not improve significantly these forecasts (Tables 14 and 15). Finally, predicting reversals gives weaker performances than forecasting crises, as previously defined. An explanation could be that risk aversion keeps increasing after the reversal, along with the development of the crisis.

7. CONCLUSION

Empirical risk aversion indicators are intended to provide a synthetic indication of market sentiment with regard to risk. Here, we try to test the relevance of the most commonly used indicators. Assuming that risk aversion increases before crises, we compare the ability of these indicators to forecast financial crises. For this, we use logit and multilogit models of currency and stock market crises successively with and without control variables. The results show that most of them are significant as leading indicators in the regressions. The multilogit models also show that risk aversion indicators remain high during the months following the crisis.

As regard to their predictive power, the results are quite different according to the type of crises. For currency crises, the indicators barely improve the prediction made by the usual control variables, such as the real exchange rate, the ratio of reserves to money supply and the real interest rates. They also perform poorly when taken alone in the regression. By contrast, in the case of stock market crises and reversals, most of the risk aversion indicators tested yield satisfactory results. The best predicting performances are obtained by a principal component analysis on risk premia.

REFERENCES

Ades A., Fuentes M., 2003. Risk aversion. Goldman Sachs, Foreign Exchange Market, October, pp. 28-31.

Baek I., Bandopadhyaya A., Du C., 2005. Determinants of market-assessed sovereign risk: economic fundamentals or market risk appetite?. Journal of International Money and Finance 24 (4), 533-548.

Berg A., Pattilo C., 1999. Are currency crises predictable? A test. IMF Staff Paper No 46-2.

Bliss R., Panigirtzoglou N., 2004. Option-implied risk aversion estimates, Journal of Finance 59 (1), 407-446.

Borio C., Kennedy N., Prowse S., 1994. Exploring aggregate asset price fluctuations across countries: measurement, determinants, and monetary policy implications. BIS Economic Paper No 40.

Boucher C., 2004. Identification et comparaison des crises boursières. In Boyer R., Dehove M., Plihon D. (Eds.), Les crises financières, Conseil d'Analyse Economique, report No 50, pp. 375-396.

Burkart O., Coudert V., 2002. Leading indicators of currency crises for emerging countries. Emerging Markets Review 3 (2), 107-133.

Bussière M., Fratzscher M., 2006. Towards a new early warning system of financial crises. Journal of International Money and Finance 25 (6), 953-973.

Campbell J., Cochrane J., 2000. Explaining the poor performance of consumption-based asset pricing models. Journal of Finance 50 (6), 2863-2878.

Campbell J., Lo A., MacKinlay A., 1997. The econometrics of financial markets. Princeton University Press, Princeton, New Jersey.

Chicago Board Options Exchange, 2004. VIX, CBOE volatility index. White Paper.

Cochrane J., 1996. A cross-sectional test of an investment-based asset pricing model. Journal of Political Economy 104 (3), 572-621.

Cochrane J., 2001. Asset pricing. Princeton University Press, Princeton, New Jersey.

Corsetti G., Pesenti P., Roubini N., 1998. Paper tigers? A model of the Asian crisis. NBER Working Paper No 6783.

Deutsche Bundesbank, 2004. Indicators of international investors' risk aversion. Monthly Report No 56-10, pp. 69-73.

Deutsche Bundesbank, 2005. Risk appetite in a dynamical financial market environment. Monthly Report No 57-10, pp. 85-97.

Dungey M., Fry R., González-Hermosillo B., Martin V., 2003. Characterizing global risk aversion for emerging markets during financial crises. IMF Working Paper No 03/251.

Fama E., French K., 1996. The CAPM is wanted, dead or alive. Journal of Finance 49 (5), 1579-1593.

Frankel J., Rose A., 1996. Currency crashes in emerging markets: empirical indicators. Journal of International Economics 41 (3-4), 351-366.

Froot K., O'Connell P., 2003. The risk tolerance of international investors, NBER Working Paper No 10157.

Gai P., Vause N., 2006. Measuring investors' risk appetite. International Journal of Central Banking 2 (1), 167-188.

Germanier B, 2003. Updated risk index. Foreign exchange note, Union des Banques Suisses, September.

Hansen L., Singleton K., 1982. Generalized instrumental variables estimation of nonlinear rational expectations models. Econometrica 50 (5), 1269-1286.

Hansen L., Singleton K., 1983. Stochastic consumption, risk aversion, and the temporal behaviour of asset returns. Journal of Political Economy 91 (2), 249-265.

Kamnisky G., Lizondo S., Reinhart C., 1997. Leading indicators of currency crises. IMF Working Paper No 97/79.

Kantor L., Caglayan M., 2002. Using equities to trade FX: introducing the LCVI. J.P. Morgan Chase Bank, Global Foreign Exchange Research, Investment Strategies No 7.

Kumar M., Persaud A., 2002. Pure contagion and investors' shifting risk appetite: analytical issues and empirical evidence. International Finance 5 (3), 401-436.

Lintner J., 1965a. The valuation of risky assets and the selection of risky investment in stock portfolios and capital budgets. Review of Economics and Statistics 47 (1), 13-37.

Lintner J., 1965b. Security prices and maximal gains from diversification. Journal of Finance 20 (4), 587-615.

Lubochinsky C., 2002. Quel crédit accorder aux spreads de crédit ?. Banque de France, Revue de la Stabilité Financière No 1, pp. 85-102.

Mankiw G., Shapiro M., 1986. Risk and return: consumption versus market beta. Review of Economics and Statistics 68 (3), 452-459.

McGuire P., Schrijvers M., 2003. Common factors in emerging market spreads. BIS Quarterly Review, December, pp. 65-78.

Mishkin F., White E., 2002. US stock market crashes and their aftermath: implications for monetary policy. NBER Working Paper No 8992.

Misina M., 2003. What does the risk-appetite index measure?. Bank of Canada Working Paper No 2003-23.

Misina M., 2006. Benchmark index of risk appetite. Bank of Canada Working Paper No 2006-16.

Patel S., Sarkar A., 1998. Crises in developed and emerging stock markets. Financial Analysts Journal 54 (6), 50-59.

Persaud A., 1996. Investors' changing appetite for risk. J.P. Morgan Securities, Global Foreign Exchange Research, July.

Pindyck R., Rubinfeld D., 1998. Econometric models and financial forecasts. McGraw-Hill, fourth edition, Boston, Massachusetts.

Prat-Gay X., McCormick J., 1999. Introducing our new "Liquidity and credit premia update". J.P. Morgan Securities, Global FX and Precious Metals Research, August.

Radelet S., Sachs J., 1998. The east Asian financial crisis: diagnosis, remedies, prospects. Brookings Paper 28 (1), 1-74.

Rosenberg D., 2003. Introducing Merrill Lynch's proprietary weekly indicators. Merrill Lynch, The Market Economist, June, pp. 4-10.

Ross S., 1976. The arbitrage theory of capital asset pricing. Journal of Economic Theory 13 (3), 341-360.

Sachs J., Tornell A., Velasco A., 1996. Financial crises in emerging markets: the lessons from 1995. Brookings Paper 27 (1), 147-199.

Scheicher M., 2003. What drives investor risk aversion? Daily evidence from the German equity market. BIS Quarterly Bulletin, June, pp. 69-77.

Sharpe W., 1964, "Capital asset prices: a theory of market equilibrium under condition of risk", Journal of Finance 19 (3), 425-442.

Sløk T., Kennedy M., 2004. Factors driving risk premia. OECD Working Paper No 385.

Tampereau Y., Teiletche J., 2001. Comment mesurer l'aversion pour le risque ?. CDC Ixis Capital Markets, Note Flash No 2001-155.

Tarashev N., Tsatsaronis K., Karampatos D., 2003. Investors' attitude towards risk: what can we learn from options?. BIS Quarterly Bulletin, June, pp. 59-68.

Wheatley S., 1988. Some tests of international equity integration. Journal of Financial Economics 21 (2), 177-212.

Wilmot J., Mielczarski P., Sweeney J., 2004. Global risk appetite index. Credit Suisse First Boston, Global Strategy Research, Market Focus, February.

Table 1 - Principal components

		1st factor	2nd factor
Eigenvalue		5.46	1.51
Proportion of explained variance		68.3%	18.9%
Proportion of cumulative explained variance		68.3%	87.1%
Eigenvectors			
United States	OAS speculative grade corporate bond spread	0.36	-0.38
	OAS investment grade corporate bond spread	0.40	-0.01
	Swap spread	0.31	0.53
Euro area	OAS speculative grade corporate bond spread	0.39	-0.31
	OAS investment grade corporate bond spread	0.41	0.06
	Swap spread	0.32	0.50
Emerging countries	EMBI Global spread	0.31	0.16
	Corporate bond spread	0.31	-0.44

Table 2 - Cross-correlations of risk aversion indicators

	Stock market GRAI	Currency RAI	Stock market RAI	PCA	VIX	LCVI	ICI
Currency GRAI	0.08	0.85***	0.07	0.00	-0.19**	0.08	0.03
Stock market GRAI		0.18*	0.85***	0.59***	0.31***	0.36***	-0.25
Currency RAI			0.15	0.11	-0.13	0.13	-0.07
Stock market RAI				0.45***	0.20*	0.26**	-0.27
PCA					0.84***	0.50***	-0.48***
VIX						0.55***	-0.32*
LCVI							0.00

*Significantly different from zero at the * 90%, ** 95%, *** 99% confidence levels.*

Table 3 - Logit estimates, currency crises, Models (1) and (2)

	Estimation period: 07/1995 – 09/2005 Number of observations = 2186				Estimation period: 12/1998 – 09/2005 Number of observations = 1521			
	Base Model (1)	Model (2) GRAI	Model (2) RAI	Model (2) VIX	Base Model (1)	Model (2) PCA	Model (2) LCVI	Model (2) ICI
Constant	1.50***	0.29***	1.43***	1.17***	-0.20	2.03**	-0.07	-2.83*
Real exchange rate	-4.47***	-4.26***	-4.42***	-5.21***	-2.93***	-5.43***	-2.86***	-3.35***
Reserves/M2	-0.96***	-0.92***	-0.92***	-0.97***	-0.89***	-0.93***	-0.91***	-0.93***
Real interest rate	1.19***	1.21***	1.21***	1.12***	1.76***	0.60***	0.78***	0.72***
Risk aversion indicator		0.86***	0.26***	0.05***		0.34***	0.00	-0.03*
Log likelihood	-508.2	-501.4	-504.0	-502.9	-289.6	-249.1	-289.6	-256.0
Pseudo R^2	0.16	0.17	0.17	0.17	0.04	0.06	0.04	0.05
Correctly predicted crises[a]	61.2%	63.4%	62.5%	62.9%	24.1%	26.6%	24.1%	26.6%
False alarms[b]	59.1%	57.6%	58.8%	57.8%	65.5%	61.1%	66.1%	65.0%

*Significantly different from zero at the * 90%, ** 95%, *** 99% confidence levels (Student's t).*
[a] *Number of crises predicted correctly as % of total number of crises.*
[b] *Number of crises wrongly correctly as % of number of crises predicted.*

Table 4 - Logit estimates, currency crises, Model (3)

	Estimation period: 07/1995 – 09/2005 Number of observations = 2186			Estimation period: 12/1998 – 09/2005 Number of observations = 1521		
	GRAI	RAI	VIX	PCA	LCVI	ICI
Constant	-2.20***	-2.20***	-2.80***	-3.00***	-3.24***	-4.54***
Risk aversion indicator	0.35***	1.11***	0.03***	0.15***	0.00	-0.02
Log likelihood	-736.9	-732.0	-647.2	-307.3	-311.1	-311.1
Pseudo R²	0.01	0.01	0.00	0.01	0.00	0.00
Correctly predicted crises[a]	0%	0.9%	0%	0%	0%	0%
False alarms[b]	n.a.	88.9%	n.a.	n.a.	n.a.	n.a.

Notes: see Table 3.
n.a.: no crisis predicted by the model.

Table 5 - Multilogit estimates, currency crises, Models (1) and (2)

	Estimation period: 07/1995 – 09/2005 Number of observations = 2391				Estimation period: 12/1998 – 09/2005 Number of observations = 1618			
	Base Model (1)	Model (2) GRAI	Model (2) RAI	Model (2) VIX	Base Model (1)	Model (2) PCA	Model (2) LCVI	Model (2) ICI
Pre-crisis period								
Constant	1.53***	1.32***	1.44***	1.18***	-0.44	1.83**	-0.30	-2.71
Real exchange rate	-4.31***	-4.21***	-4.36***	-5.04***	-2.72***	-5.28***	-2.67***	-3.04***
Reserves/M2	-0.97***	-0.94***	-0.93***	-0.98***	-0.99***	-1.04***	-1.00***	-1.03***
Real interest rate	0.92***	0.96***	0.96***	0.86***	0.83***	0.71***	0.84***	0.80***
Risk aversion indicator		0.98***	0.31***	0.04***		0.35***	0.00	-0.03
Post-crisis period								
Constant	-3.18***	-3.27***	-3.25***	-3.22***	-3.51***	-3.75***	-3.91***	0.16
Real exchange rate	0.58**	0.67**	0.64**	0.55**	0.33	0.58	0.39	0.43
Reserves/M2	-0.93***	-0.91***	-0.91***	-0.92***	1.10***	-1.14***	-1.08***	-1.08***
Real interest rate	0.65***	0.66***	0.66***	0.63***	0.82***	0.90***	0.81***	0.86***
Risk aversion indicator		0.55**	0.13	0.00		-0.17**	0.01	0.03**
Log likelihood	-1382.9	-1098.0	-1101.6	-1103.5	-540.0	-526.2	-539.2	-535.8
Pseudo R²	0.23	0.23	0.23	0.23	0.15	0.17	0.15	0.15
Correctly predicted crises[a]	60.8%	61.2%	59.9%	61.6%	25.3%	29.1%	29.1%	31.7%
False alarms[b]	57.4%	58.1%	58.3%	58.2%	69.2%	68.9%	66.2%	65.3%

Notes: see Table 3.

Table 6 - Multilogit estimates, currency crises, Model (3)

	Estimation period: 07/1995 – 09/2005 Number of observations = 2460			Estimation period: 12/1998 – 09/2005 Number of observations = 1640		
	GRAI	RAI	VIX	PCA	LCVI	ICI
Pre-crisis period						
Constant	-2.19***	-2.19***	-2.79***	-3.00***	-3.24***	-4.56***
Risk aversion indicator	1.10***	0.34***	0.03**	0.15***	0.01	-0.02
Post-crisis period						
Constant	-2.28***	-2.29***	-3.26***	-2.75***	-3.56***	-1.26
Risk aversion indicator	0.28	0.10	0.04***	0.10*	0.02***	0.01
Log likelihood	-1452.9	-1442.4	-1452.9	-680.1	-674.8	-678.8
Pseudo R²	0.01	0.01	0.01	0.01	0.01	0.00
Correctly predicted crises[a]	0%	0%	0%	0%	0%	0%
False alarms[b]	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Notes: see Table 3.
n.a.: no crisis predicted by the model.

Table 7 - Logit estimates, stock market crises, Models (1) and (2)

	Estimation period: 12/1998 – 09/2005 Number of observations = 1950						
	Base Model (1)	Model (2) GRAI	Model (2) RAI	Model (2) VIX	Model (2) PCA	Model (2) LCVI	Model (2) ICI
Constant	-2.97***	-2.96***	-2.84***	-3.79***	-3.37***	-2.51***	-5.74***
PER	0.43***	0.46***	0.44***	0.42***	0.43***	0.41***	0.42***
Returns	-2.33***	-2.22***	-2.22**	-2.18***	-1.80***	-2.36***	-2.28***
Real interest rate	-0.20**	-0.25***	-0.25***	-0.23***	-0.33***	-0.16*	-0.21**
Risk aversion indicator		1.27***	0.60***	0.04***	0.53***	-0.01**	0.03***
Log likelihood	-555.5	-540.6	-538.8	-552.1	-497.0	-552.5	-552.2
Pseudo R²	0.33	0.35	0.35	0.34	0.40	0.34	0.34
Correctly predicted crises[a]	84.4%	86.0%	84.1%	84.4%	86.6%	84.8%	84.4%
False alarms[b]	49.9%	48.3%	48.1%	48.8%	48.5%	50.0%	48.9%

Notes: see Table 3.

Table 8 - Logit estimates, stock market crises, Model (3)

	Estimation period: 12/1998 – 09/2005 Number of observations = 1950					
	GRAI	RAI	VIX	PCA	LCVI	ICI
Constant	-1.66***	-1.54***	-4.86***	-2.40***	-1.44***	-6.94***
Risk aversion indicator	1.78***	0.97***	0.14***	0.68***	0.00	-0.06***
Log likelihood	-822.9	-816.0	-784.4	-669.1	-871.4	-848.2
Pseudo R²	0.05	0.06	0.09	0.21	0.01	-0.02
Correctly predicted crises[a]	56.7%	66.4%	43.3%	74.5%	0%	26.5%
False alarms[b]	73.2%	70.6%	77.5%	61.9%	n.a.	84.1%

Notes: see Table 3.
n.a.: no crisis predicted by the model.

Table 9 - Multilogit estimates, stock market crises, Models (1) and (2)

	Estimation period: 12/1998 – 09/2005 Number of observations = 2214						
	Base Model (1)	Model (2) GRAI	Model (2) RAI	Model (2) VIX	Model (2) PCA	Model (2) LCVI	Model (2) ICI
Pre-crisis period							
Constant	-2.88***	-2.90***	-2.77***	-3.70***	-3.25***	-2.50***	-6.81***
PER	0.43***	0.46***	0.44***	0.42***	0.41***	0.42***	0.43***
Returns	-2.21***	-2.11***	-2.12***	-2.05***	-1.75***	-2.23***	-2.18***
Real interest rate	-0.17**	-0.23***	-0.25***	-0.20**	-0.30***	-0.13	-0.18**
Risk aversion indicator		1.46***	0.78***	0.04**	0.49***	-0.01*	-0.04***
Post-crisis period							
Constant	-3.99***	-4.26***	-4.21***	-4.85***	-3.95***	-3.27***	-2.21
PER	0.26***	0.22***	0.25***	0.26***	0.24***	0.23***	0.24***
Returns	-3.02***	-3.19***	-3.06***	-2.84**	-3.04***	-3.07***	-3.00***
Real interest rate	-0.45***	-0.43***	-0.41***	-0.47***	-0.46***	-0.36***	-0.45***
Risk aversion indicator		-1.50***	-0.48***	0.04**	-0.04	-0.02***	0.02
Log likelihood	-1116.7	-1063.3	-1059.2	-1111.8	-1043.5	-1110.1	-1106.3
Pseudo R²	0.46	0.50	0.50	0.47	0.52	0.47	0.47
Correctly predicted crises[a]	84.4%	86.0%	82.6%	84.4%	86.9%	85.1%	83.8%
False alarms[b]	49.9%	48.3%	48.5%	49.4%	48.8%	49.8%	49.2%

Notes: see Table 3.

Table 10 - Multilogit estimates, stock market crises, Model (3)

	Estimation period: 12/1998 – 09/2005 Number of observations = 2214					
	GRAI	RAI	VIX	PCA	LCVI	ICI
Pre-crisis period						
Constant	-1.66***	-1.54***	-4.98***	-2.38***	-1.44***	-7.34***
Risk aversion indicator	1.89***	1.00***	0.15***	0.67***	0.00	-0.06***
Post-crisis period						
Constant	-1.85***	-1.96***	-5.98***	-1.95***	-1.28***	-3.86***
Risk aversion indicator	-0.29	-0.32***	0.18***	0.32***	-0.01***	-0.02*
Log likelihood	-1624.4	-1609.3	-1509.8	-1449.6	-1675.3	-1654.6
Pseudo R²	0.05	0.06	0.15	0.20	0.01	0.02
Correctly predicted crises[a]	56.7%	66.4%	43.3%	79.8%	0%	31.8%
False alarms[b]	73.2%	70.6%	77.5%	60.7%	n.a.	81.7%

Notes: see Table 3.
n.a.: no crisis predicted by the model.

Table 11 - Logit estimates, stock market crises, Models (2) and (3) with the 8 spreads used in the PCA

		Estimation period: 12/1998 – 09/2005 Number of observations = 1950	
		Model (2)	Model (3)
Constant		-6.33***	-7.14***
PER		0.34***	
Returns		-1.61***	
Real interest rate		-0.21**	
United States	OAS speculative grade corporate bond spread	-0.04***	-0.06***
	OAS investment grade corporate bond spread	0.08***	0.10***
	Swap spread	0.02	0.01
Euro area	OAS speculative grade corporate bond spread	0.01**	0.02***
	OAS investment grade corporate bond spread	$1.76 \cdot 10^{-3}$	0.05**
	Swap spread	-0.07***	-0.10***
Emerging countries	EMBI Global spread	$-2.40 \cdot 10^{-3}$**	$-1.46 \cdot 10^{-3}$**
	Corporate bond spread	$3.95 \cdot 10^{-3}$***	$4.83 \cdot 10^{-3}$***
Log likelihood		-443.4	-537.9
Pseudo R²		0.45	0.35
Correctly predicted crises[a]		88.2%	76.3%
False alarms[b]		44.7%	50.6%

Notes: see Table 4.

Table 12 - Logit estimates, stock market reversals, Models (1) and (2)

	Estimation period: 12/1998 – 09/2005 Number of observations = 1970						
	Base Model (1)	Model (2) GRAI	Model (2) RAI	Model (2) VIX	Model (2) PCA	Model (2) LCVI	Model (2) ICI
Constant	-1.92***	-1.84***	-1.80***	-4.60***	-2.23***	-4.81***	-7.16***
PER	0.26***	0.26***	0.26***	0.17***	0.11***	0.24***	0.24***
Returns	0.77***	0.87**	0.81***	0.97***	1.18***	0.84***	0.78***
Real interest rate	0.58***	0.52***	0.55***	0.43***	0.34***	0.22**	0.55***
Risk aversion indicator		1.68***	0.46***	0.12***	0.57***	0.06***	0.05***
Log likelihood	-703.9	-673.0	-692.1	-661.8	-594.6	-616.3	-686.1
Pseudo R²	0.11	0.15	0.13	0.16	0.23	0.21	0.13
Correctly predicted crises[a]	51.2%	53.0%	48.8%	59.0%	69.5%	65.6%	53.3%
False alarms[b]	65.1%	65.1%	67.6%	61.3%	57.2%	59.3%	63.8%

Notes: see Table 3.

Table 13 - Logit estimates, stock market reversals, Model (3)

	Estimation period: 12/1998 – 09/2005 Number of observations = 1970					
	GRAI	RAI	VIX	PCA	LCVI	ICI
Constant	-1.71***	-1.67***	-3.14***	-1.93***	-4.42***	-6.91***
Risk aversion indicator	1.26***	0.38***	0.06***	0.31***	0.05***	0.05***
Log likelihood	-793.5	-805.1	-796.2	-758.1	-707.7	-795.4
Pseudo R²	0.02	0.01	0.02	0.06	0.11	0.02
Correctly predicted crises[a]	28.1%	0%	2.8%	35.1%	45.6%	25.6%
False alarms[b]	71.5%	n.a.	97.2%	80.2%	72.6%	73.4%

Notes: see Table 3.
n.a.: no crisis predicted by the model.

Table 14 - Multilogit estimates, stock market reversals, Models (2) and (3)

	Estimation period: 12/1998 – 09/2005 Number of observations = 2214						
	Base Model (1)	Model (2) GRAI	Model (2) RAI	Model (2) VIX	Model (2) PCA	Model (2) LCVI	Model (2) ICI
Pre-crisis period							
Constant	-1.92***	-1.84***	-1.80***	-4.70***	-2.21***	-4.88***	-7.30***
PER	0.26***	0.26***	0.26***	0.17**	0.10	0.24***	0.24***
Returns	0.76***	0.86***	0.80***	0.97**	1.16***	0.83***	0.78***
Real interest rate	0.59***	0.54***	0.56***	0.43***	0.35**	0.23***	0.56***
Risk aversion indicator		1.63***	0.46***	0.13***	0.56***	0.06***	0.06***
Post-crisis period							
Constant	-2.03***	-2.42***	-1.95***	-3.54***	-2.61***	-3.37***	-11.94***
PER	-0.08	-0.03	-0.12	-0.11	-0.20**	-0.05***	-0.11
Returns	-0.38***	-0.22**	-0.28***	-0.16**	0.25***	-0.35***	-0.33***
Real interest rate	0.64***	0.55***	0.57***	0.58***	0.50**	0.47***	0.62***
Risk aversion indicator		4.24***	1.34***	0.07***	0.70***	0.03***	0.10***
Log likelihood	-1420.5	-1262.0	-1343.0	-1370.2	-1210.7	-1316.4	-1358.6
Pseudo R²	0.14	0.28	0.21	0.19	0.32	0.23	0.20
Correctly predicted crises[a]	51.2%	53.0%	49.1%	59.3%	69.5%	66.7%	53.3%
False alarms[b]	65.4%	65.1%	67.3%	61.7%	57.0%	58.9%	63.9%

Notes: see Table 3.

Table 15 - Multilogit estimates, stock market reversals, Model (3)

	Estimation period: 12/1998 – 09/2005 Number of observations = 2214					
	GRAI	RAI	VIX	PCA	LCVI	ICI
Pre-crisis period						
Constant	-1.71***	-1.67***	-3.27***	-1.94***	-4.49***	-6.98***
Risk aversion indicator	1.25***	0.38***	0.07***	0.33***	0.05***	0.05***
Post-crisis period						
Constant	-2.36***	-1.88***	-4.00***	-2.70***	-3.68***	-11.89***
Risk aversion indicator	4.35***	1.47***	0.09***	0.66***	0.04***	0.10***
Log likelihood	-1410.3	-1490.7	-1537.0	-1389.9	-1446.1	-1513.5
Pseudo R²	0.15	0.08	0.04	0.17	0.12	0.06
Correctly predicted crises[a]	28.1%	0%	3.9%	35.1%	45.6%	25.6%
False alarms[b]	71.53%	n.a.	96.3%	80.2%	72.6%	73.4%

Notes: see Table 3.
n.a.: no crisis predicted by the model.

APPENDIX 1: THE DATABASE

The GRAI

The currency GRAI comprises 12 to 15 currencies quoted against the dollar according to the periods for which the data are available: the Norwegian krone, the Czech koruna, the Swedish krona, the Deutsche Mark then the euro from 1999, the Australian dollar, the Canadian dollar, the Hong Kong dollar, the Singapore dollar, the New Zealand dollar, the Swiss franc, pound sterling, the Mexican peso, the South African rand, the yen and the Polish zloty.

The currency RAI is made up of 12 currencies over the whole period as a different number of series over time would produce abrupt changes in the regression coefficient, which would distort the calculation.

The stock market GRAI and RAI include the major stock market indices of 27 developed and emerging economies: Argentina, Australia, Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Indonesia, Ireland, Italy, Japan, Malaysia, Netherlands, Norway, New Zealand, Portugal, South Africa, Spain, Sweden, Turkey, the United Kingdom and the United States.

Components of the PCA

Eight risk premia are used in the PCA. The data are taken from Bloomberg:

- 4 OAS corporate bond spreads for the euro area and the United States:[7] for each area, one spread for investment grade and another for speculative grade. These spreads are calculated by Merrill Lynch;

- 2 spreads for emerging markets: first, the EMBI Global,[8] representing the risk premium on their dollar-denominated external sovereign debt, calculated since mid-1998 by J.P. Morgan on a large panel of emerging market countries; and second, an index of corporate debt, denominated in dollars or euro and issued abroad, of a large number of emerging market countries. This index is calculated by the bank Merrill Lynch and satisfies certain liquidity conditions;

- 2 swap spreads, one for the euro area and one for the United States.

[7] For this, we use bonds that have an optional component – the option adjusted duration – to calculate the credit spread between two bonds with the same maturity (Lubochinsky, 2002).

[8] The Emerging Markets Bond Index Global (EMBI Global) is an index that represents the average price of bonds in emerging market countries.

Crisis indicators

Currency crisis

The countries selected are the following: Argentina, Brazil, Bulgaria, Chile, Colombia, Czech Republic, Estonia, Hungary, Indonesia, Latvia, Lithuania, Mexico, Philippines, Poland, Romania, Singapore, South Korea, Thailand, Uruguay and Venezuela.

The sample period is from March 1995 to September 2005.

The data were taken from the IMF's International Financial Statistics (IFS) database for the 1995-2005 period as monthly data (quarterly data were made monthly by means of linear interpolation): total reserves minus gold, line 1 l.d; money, line 34, quasi-money, line 35, to obtain the reserves/M2 ratio; real exchange rate, line ae, consumer prices, line 64, to calculate the real exchange rate; and money market rate, lines 60, 60b or 60a (depending on the availability of data and in this order of preference), to calculate the real interest rate (with the aid of consumer prices).

Stock market crisis

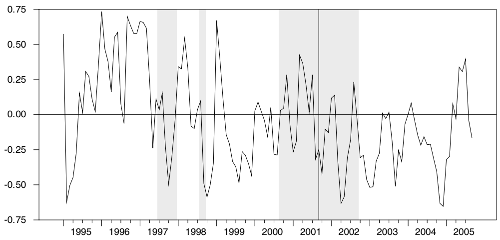
The countries selected are the following: Argentina, Australia, Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Indonesia, Ireland, Italy, Japan, Malaysia, Netherlands, Norway, New Zealand, Portugal, South Africa, Spain, Sweden, Turkey, the United Kingdom, and the United States.

The estimation period is from December 1995 to September 2005.

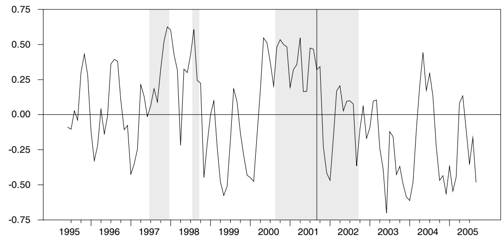
The indices, taken from Bloomberg, are the following: DAX (Germany), S&P/TSX Composite (Canada), DJIA (United States), CAC 40 (France), OMX Stockholm 30 (Sweden), AEX (Pays-Bas), BEL20 (Belgium), MIB30 (Italia), Nikkei (Japan), FTSE 100 (United Kingdom), IBEX 35 (Spain), PSI General (Portugal), OMX Copenhagen 20 (Denmark), OMX Helsinki (Finland), ATX (Austria), Irish overall (Ireland), OBX (Norway), ASE General (Greece), ISE National 100 (Turkey), Johannesburg Stock Exchange (South Africa), S&P/ASX 200 (Australia), NZX Top 10 (New Zealand), Hang Seng (Hong Kong), Kuala Lumpur Composite (Malaysia), Jakarta Composite (Indonesia), MERVAL (Argentina), BOVESPA Stock (Brazil). The returns have been calculated using these indices. The PER on these indices have also been obtained from Bloomberg. Interest rates have been taken from the IMF's IFS database and calculated in the same way as for currency crises.

APPENDIX 2: RISK AVERSION INDICATORS GRAPHS

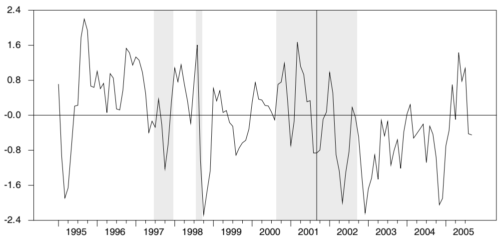
GRAI calculated on the foreign exchange market



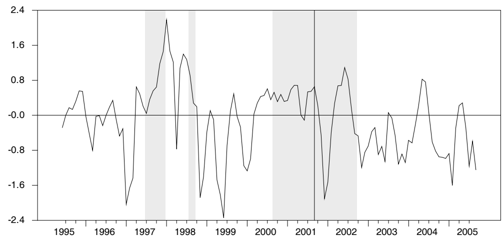
GRAI calculated on the stock market



RAI calculated on the foreign exchange market

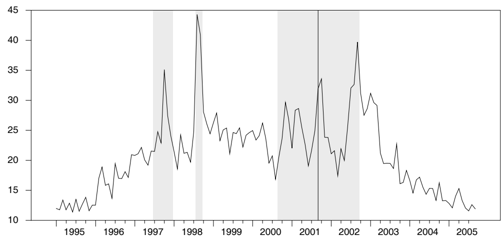


RAI calculated on the stock market

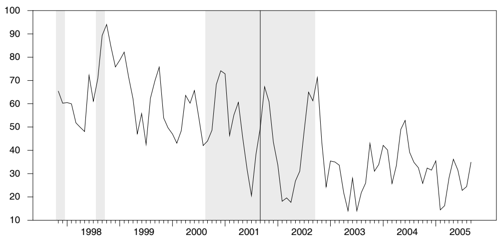


Risk aversion indicator measured
by the first component of the PCA

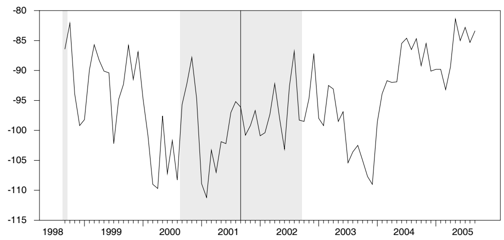
VIX



LCVI



ICI



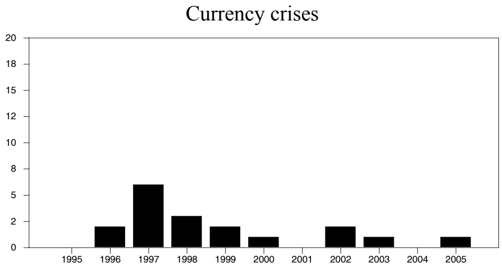
Note: vertical columns: Asian crisis (07/1997 – 12/1997), Russian crisis and failure of LTCM (08/1998 – 09/1998) and downtrend on the main stock markets (09/2000 – 09/2002). Vertical line: terrorist attacks September, 11th, 2001.

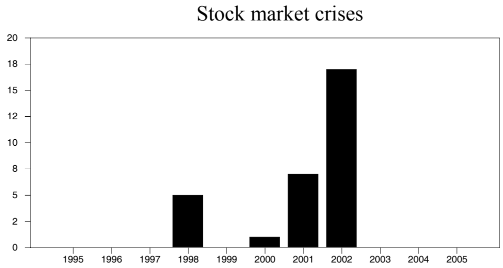
APPENDIX 3: CURRENCY AND STOCK MARKET CRISES

1. Identification of crises

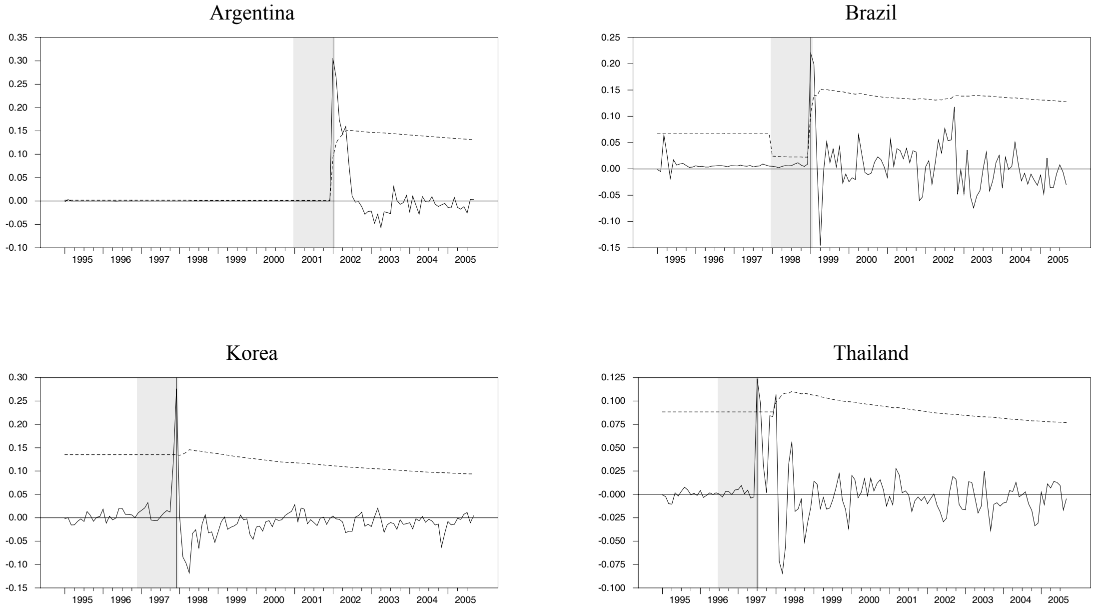
Estimation period: 07/1995 – 09/2005			
Currency crises		Stock market crises	
Argentina	January 2002	Argentina	May 2002
Brazil	January 1999	Australia	September 2002
Bulgaria	May 1996	Austria	September 1998
Chilli		Belgium	September 2002
Colombia	September 1998	Brazil	July 2002
Czech Republic	May 1997 et August 1998	Canada	September 2001 and September 2002
Estonia	June 2003	Denmark	July 2002
Hungary		Finland	August 2001
Indonesia	April 1997	France	July 2002
Korea	December 1997	Germany	September 2002
Latvia		Greece	September 2001
Lithuania		Hong Kong	July 1998
Mexico		Indonesia	
Philippines	September 1997	Ireland	July 2002
Poland	August 1998 and March 2005	Italy	July 2002
Romania	July 1996 and November 1999	Japan	September 2001
Singapore	December 1997	Malaysia	January 1998
Thailand	July 1997	Netherlands	September 2002
Uruguay	April 2002	New Zealand	August 1998
Venezuela	February 2002	Norway	September 2002
		Portugal	September 2001 and September 2002
		South Africa	August 1998
		Spain	September 2001 and September 2002
		Sweden	June 2002
		Turkey	November 2000
		United Kingdom	July 2002
		United States	September 2001 and September 2002

Number of identified crises by year



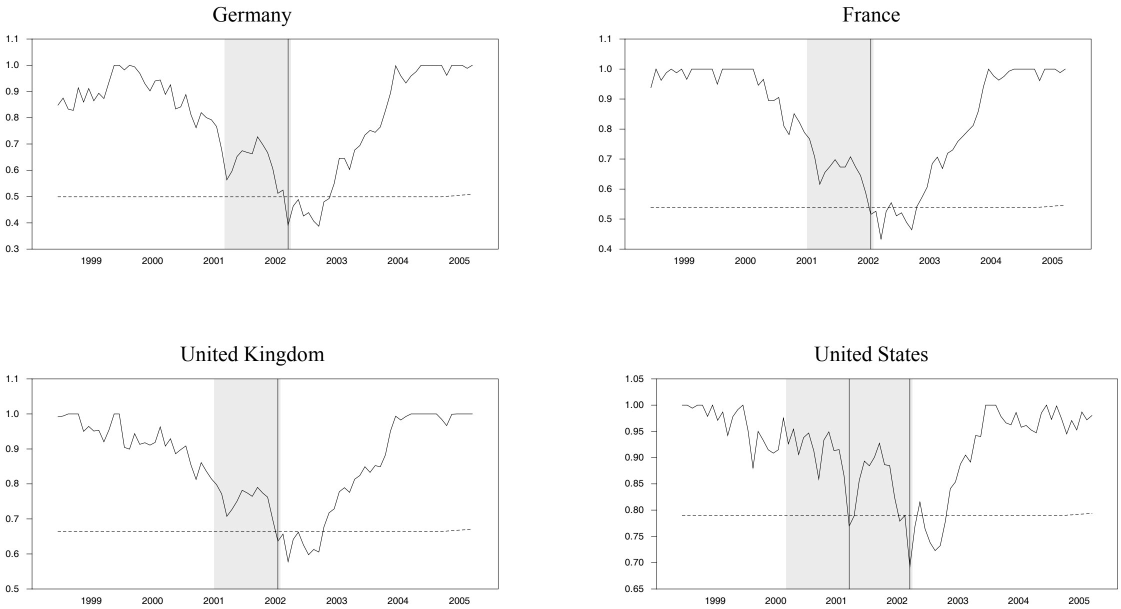


Identification of currency crises: pressure index (full line) and crisis threshold (dotted line) for 4 selected countries



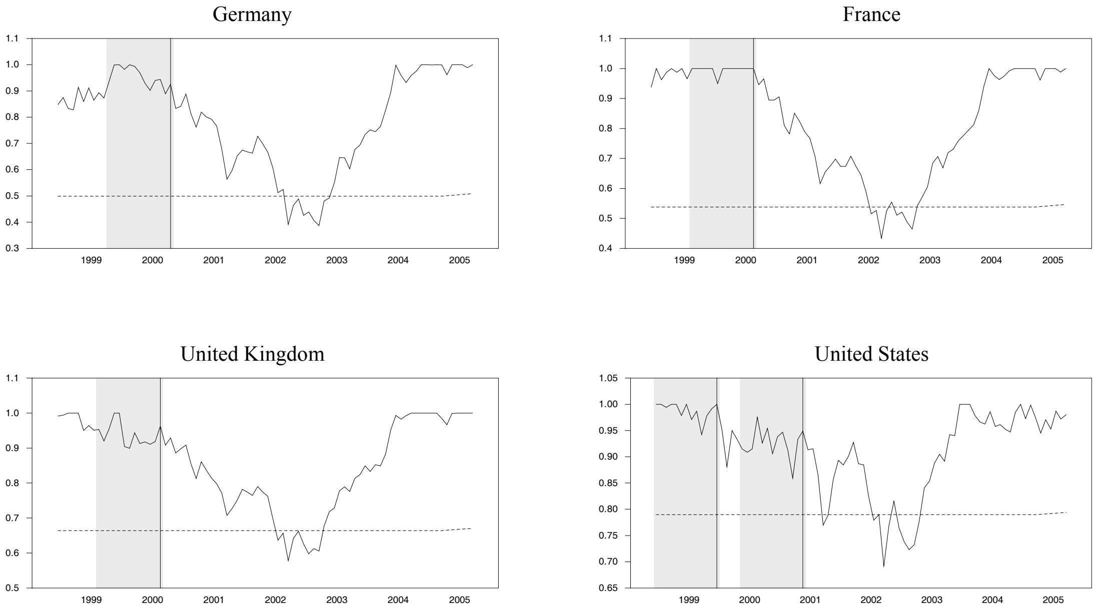
Note: vertical lines: identified crises. Vertical columns: pre-crisis periods.

Identification of stock market crises: CMAX (full line) and crisis threshold (dotted line) for 4 selected countries



Note: vertical lines: identified crises. Vertical columns: pre-crisis periods.

Identification of stock market reversals: CMAX (full line) and crisis threshold (dotted line) for 4 selected countries

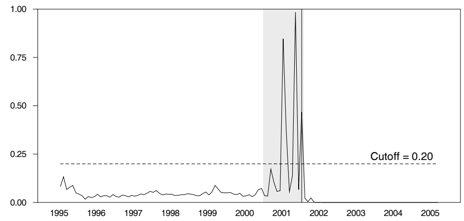


Note: vertical lines: identified reversals. Vertical columns: pre-crisis periods.

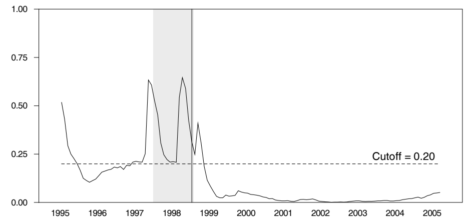
2. Simulation with control variables

Currency crisis probabilities for 4 selected countries
Logit estimates, Model (1)

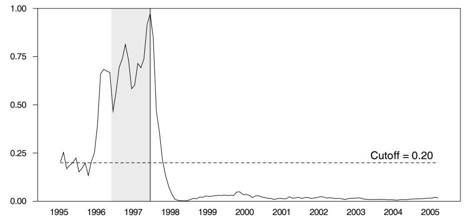
Argentina



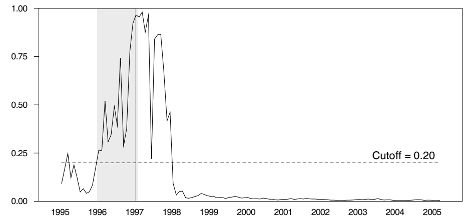
Brazil



Korea



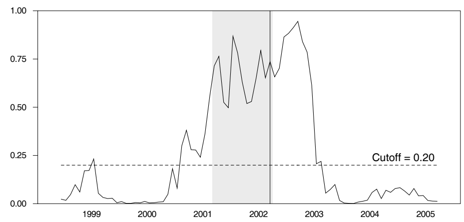
Thailand



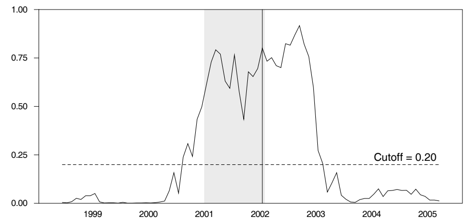
Note: vertical lines: identified crises. Vertical columns: pre-crisis periods.

Stock market crisis probabilities for 4 selected countries
Logit estimates, Model (1)

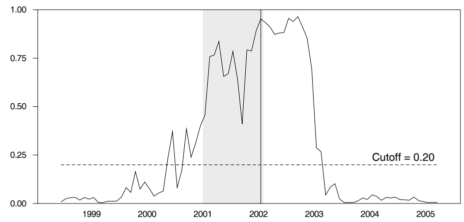
Germany



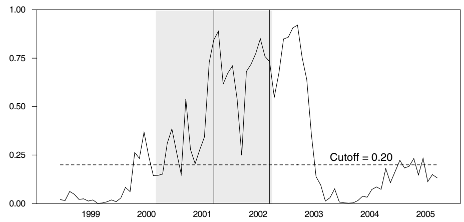
France



United Kingdom



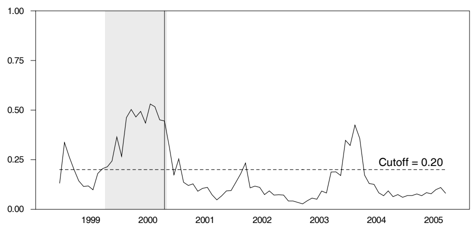
United States



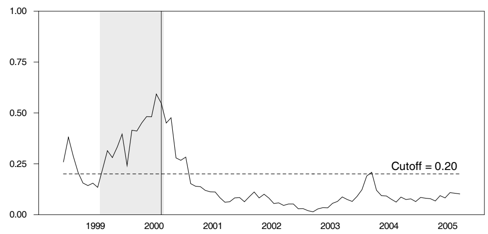
Note: vertical lines: identified crises. Vertical columns: pre-crisis periods.

Stock market reversal probabilities for 4 selected countries
Logit estimates, Model (1)

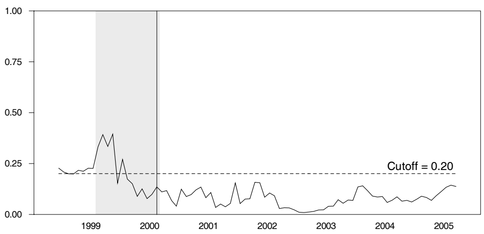
Germany



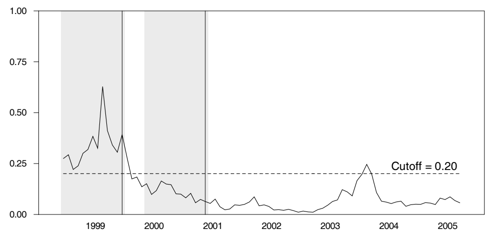
France



United Kingdom



United States



Note: vertical lines: identified reversals. Vertical columns: pre-crisis periods.

List of working papers released by CEPII[9]

No	*Title*	*Authors*
2007-01	World Growth and International Capital Flows in the XXIst Century: A prospective analysis with the INGENUE 2 model[10]	M. Aglietta, V. Borgy J. Château, M. Juillard J. le Cacheux, G. Le Garrec &. V. Touzé
2006-27	Current Account Reversals and Long Term Imbalances : Application to the Central and Eastern European Countries	K. Benhima & O. Havrylchyk
2006-26	Do Legal Origins and Brankruptcy Laws : the European Experience (1808-1914)	J. Sgard
2006-25	Taux d'intérêt et marchés boursiers : une analyse empirique de l'intégration financière internationale	V. Borgy & V. Mignon
2006-24	On Legal Origins & Bankruptcy Laws : the European Experience (1808-1914)	J. Sgard
2006-23	Market Access Impact on Individual Wage: Evidence from China	L. Hering & S. Poncet
2006-22	FDI in Chinese Cities: Spillovers and Impact on Growth	N. Madariaga & S. Poncet
2006-21	Are Financial Distortions an Impediment to Economic Growth? Evidence from China	A. Guariglia & S. Poncet
2006-20	World Consistent Equilibrium Exchange Rates	A. Bénassy-Quéré, A. Lahrèche-Révil & V. Mignon
2006-19	Institutions and Bilateral Asset Holdings	V. Salins & A. Bénassy-Quéré
2006-18	Vertical Production Networks: Evidence from France	M. Fouquin, L. Nayman

[9] Working papers are circulated free of charge as far as stocks are available; thank you to send your request to CEPII, Sylvie Hurion, 9, rue Georges-Pitard, 75015 Paris, or by fax : (33) 01 53 68 55 04 or by e-mail sylvie.hurion @ cepii.fr. Also available on: \\www.cepii.fr. Working papers with * are out of print. They can nevertheless be consulted and downloaded from this website.

[9] Les documents de travail sont diffusés gratuitement sur demande dans la mesure des stocks disponibles. Merci d'adresser votre demande au CEPII, Sylvie Hurion, 9, rue Georges-Pitard, 75015 Paris, ou par fax : (33) 01 53 68 55 04 ou par e-mail sylvie.hurion @ cepii.fr. Egalement disponibles sur : \\www.cepii.fr. Les documents de travail comportant * sont épuisés. Ils sont toutefois consultable sur le web CEPII.

[10] We thank Agnès Benassy-Quéré for her valuable remarks and suggestions on a previous version of the paper.

		& L. Wagner
2006-17	Import Prices, Variety and the Extensive Margin of Trade	G. Gaulier & I. Méjean
2006-16	The Long Term Growth Prospects of the World Economy: Horizon 2050	S. Poncet
2006-15	Economic Integration in Asia: Bilateral Free Trade Agreements Versus Asian Single Market	M. H. Bchir & M. Fouquin
2006-14	Foreign Direct Investment in China: Reward or Remedy?	O. Havrylchyk & S. Poncet
2006-13	Short-Term Fiscal Spillovers in a Monetary Union	A. Bénassy-Quéré
2006-12	Can Firms' Location Decisions Counteract the Balassa-Samuelson Effect?	I. Méjean
2006-11	Who's Afraid of Tax Competition? Harmless Tax Competition from the New European Member States	A. Lahrèche-Révil
2006-10	A Quantitative Assessment of the Outcome of the Doha Development Agenda	Y. Decreux & L. Fontagné
2006-09	Disparities in Pension Financing in Europe: Economic and Financial Consequences	J. Château & X. Chojnicki
2006-08	Base de données CHELEM-BAL du CEPII	H. Boumellassa & D. Ünal-Kesenci
2006-07	Deindustrialisation and the Fear of Relocations in the Industry	H. Boulhol & L. Fontagné
2006-06	A Dynamic Perspective for the Reform of the Stability and Gowth Pact	C. Deubner
2006-05	China's Emergence and the Reorganisation of Trade Flows in Asia	G. Gaulier, F. Lemoine & D. Ünal-Kesenci
2006-04	Who Pays China's Bank Restructuring Bill?	G. Ma
2006-03	Structural Determinants of the Exchange-Rate Pass-Through	G. Gaulier, A. Lahrèche-Révil & I. Méjean
2006-02	Exchange-Rate Pass-Through at the Product Level	G. Gaulier, A. Lahrèche-Révil & I. Méjean
2006-01	Je t'aime, moi non plus : Bilateral Opinions and International Trade	A.C. Disdier & T. Mayer
2005-23	World Trade Competitiveness: A Disaggregated View by Shift-Share Analysis	A. Cheptea, G. Gaulier & S. Zignago
2005-22	Chômage et réformes du marché du travail au Japon	E. Dourille-Feer

2005-21	Profitability of Foreign and Domestic Banks in Central and Eastern Europe: Does the Mode of Entry Matter?	O. Havrylchyk & E. Jurzyk
2005-20	ECB Governance in an Enlarged Eurozone	A. Bénassy-Quéré & E. Turkisch
2005-19	What Are EU Trade Preferences Worth for Sub-Saharan Africa and Other Developing Countries?	F. Candau & S. Jean
2005-18	Binding Overhang and Tariff-Cutting Formulas	M.H. Bchir, S. Jean & D. Laborde
2005-17	International Trade and Income Distribution: Reconsidering the Evidence	I. Bensidoun, S. Jean & A. Sztulman
2005-16	China and the Relationship between the Oil Price and the Dollar	A. Bénassy-Quéré, V. Mignon & A. Penot
2005-15	Consequences of Alternative Formulas for Agricultural Tariff Cuts	S. Jean, D. Laborde & W. Martin
2005-14	Is Erosion of Tariff Preferences a Serious Concern?	A. Bouët, L. Fontagné & S. Jean
2005-13	The Consequences of Agricultural Trade Liberalization for Developing Countries: Distinguishing Between Genuine Benefits and False Hopes	J.C. Bureau, S. Jean A. Matthews
2005-12	From Bound Duties to Actual Protection: Industrial Liberalisation in the Doha Round	M.H. Bchir, L. Fontagné & S. Jean
2005-11	Impact de l'ouverture financière sur les inégalités internes dans les pays émergents	A. Bénassy-Quéré & V. Salins
2005-10	Disentangling Horizontal and Vertical Intra-Industry Trade	L. Fontagné, M. Freudenberg & G. Gaulier
2005-09	China's Integration in East Asia: Production Sharing, FDI & High-Tech Trade	G. Gaulier, F. Lemoine D. Ünal-Kesenci
2005-08	Tax Competition and Public Input	A. Bénassy-Quéré, N. Gobalraja & A. Trannoy
2005-07	Trade Liberalisation, Growth and Poverty in Senegal: A Dynamic Microsimulation CGE Model Analysis	N. Annabi, F. Cissé, J. Cockburn & B. Decaluwé
2005-06	Migration, Trade and Wages	A. Hijzen & P. Wright
2005-05	Institutional Determinants of Foreign Investment	A. Bénassy-Quéré, M. Coupet & T. Mayer

2005-04	L'économie indienne : changements structurels et perspectives à long terme	S. Chauvin & F. Lemoine
2005-03	Programme de travail du CEPII pour 2005	
2005-02	Market Access in Global and Regional Trade	T. Mayer & S. Zignago
2005-01	Real Equilibrium Exchange Rate in China	V. Coudert & C. Couharde
2004-22	A Consistent, *ad-valorem* Equivalent Measure of Applied Protection Across the World: The MAcMap-HS6 Database	A. Bouët, Y. Decreux, L. Fontagné, S. Jean & D. Laborde
2004-21	IMF in Theory: Sovereign Debts, Judicialisation and Multilateralism	J. Sgard
2004-20	The Impact of Multilateral Liberalisation on European Regions: a CGE Assessment	S. Jean & D. Laborde
2004-19	La compétitivité de l'agriculture et des industries agroalimentaires dans le Mercosur et l'Union européenne dans une perspective de libéralisation commerciale	N. Mulder, A. Vialou, B. David, M. Rodriguez & M. Castilho
2004-18	Multilateral Agricultural Trade Liberalization: The Contrasting Fortunes of Developing Countries in the Doha Round	A. Bouët, J.C. Bureau, Y. Decreux & S. Jean
2004-17	UK in or UK out? A Common Cycle Analysis between the UK and the Euro Zone	J. Garnier
2004-16	Regionalism and the Regionalisation of International Trade	G. Gaulier, S. Jean & D. Ünal-Kesenci
2004-15	The Stock-Flow Approach to the Real Exchange Rate of CEE Transition Economies	B. Egert, A. Lahrècche-Révil & K. Lommatzsch
2004-14	Vieillissement démographique, épargne et retraite : une analyse à l'aide d'un modèle d'équilibre général à agents hétérogènes	C. Bac & J. Chateau
2004-13	Burden Sharing and Exchange-Rate Misalignments within the Group of Twenty	A. Bénassy-Quéré, P. Duran-Vigneron, A. Lahrèche-Révil & V. Mignon
2004-12	Regulation and Wage Premia	S. Jean & G. Nicoletti
2004-11	The Efficiency of Fiscal Policies: a Survey of the Literature	S. Capet
2004-10	La réforme du marché du travail en Allemagne : les	S. Capet

	enseignements d'une maquette	
2004-09	Typologie et équivalence des systèmes de retraites	P. Villa
2004-08	South – South Trade: Geography Matters	S. Coulibaly & L. Fontagné
2004-07	Current Accounts Dynamics in New EU Members: Sustainability and Policy Issues	P. Zanghieri
2004-06	Incertitude radicale et choix du modèle	P. Villa
2004-05	Does Exchange Rate Regime Explain Differences in Economic Results for Asian Countries?	V. Coudert & M. Dubert
2004-04	Trade in the Triad: How Easy is the Access to Large Markets?	L. Fontagné, T. Mayer & S. Zignago
2004-03	Programme de travail du CEPII pour 2004	
2004-02	Technology Differences, Institutions and Economic Growth: a Conditional Conditional Convergence	H. Boulhol
2004-01	Croissance et régimes d'investissement	P. Villa

CEPII
DOCUMENTS DE TRAVAIL / WORKING PAPERS

Si vous souhaitez recevoir des Documents de travail,
merci de remplir le coupon-réponse ci-joint et de le retourner à :

Should you wish to receive copies of the CEPII's Working papers,
just fill the reply card and return it to:

Sylvie HURION – Publications
CEPII – 9, rue Georges-Pitard – 75740 Paris – Fax : (33) 1.53.68.55.04
sylvie.hurion@cepii.fr

M./Mme / Mr./Mrs ....

Nom-Prénom / Name-First name ....

Titre / Title ....

Service / Department...

Organisme / Organisation ....

Adresse / Address..

Ville & CP / City & post code..
Pays / Country.. Tél...
Your e-mail ....

Désire recevoir les **Document de travail** du CEPII n° :

Wish to receive the ***CEPII's Working Papers No****:*...

....

....

....

....

....

....

....

....

☐ Souhaite être placé sur la liste de diffusion permanente (**pour les bibliothèques**)
Wish to be placed on the standing mailing list ***(for Libraries)****.*