

Does risk aversion drive financial crises? Testing the predictive power of empirical indicators

Virginie Coudert ^{a,b,c}, Mathieu Gex ^{a,d,*}

^a Banque de France, DGO, DCSF, 31, rue, Croix des Petits champs, 75001 Paris, France

^b CEPN, Université Paris 13, France

^c CEPII, 9 rue Georges Pitard, 75015 Paris, France

^d CERAG, Université Grenoble 2, France

Received 26 October 2006; received in revised form 8 March 2007; accepted 4 June 2007

Available online 14 June 2007

Abstract

There are several types of risk aversion indicators used by financial institutions. 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. © 2007 Elsevier B.V. All rights reserved.

JEL classification: C33; E44; F37; G12

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

1. Introduction

Risk aversion can be precisely defined within the framework of asset pricing models (Campbell et al., 1997; Cochrane, 2001). In this context, any risk premium can be decomposed into two components: a “price of risk”, which is common to all financial assets, and a “quantity of risk”, which is specific to each asset. Risk aversion can be assessed by 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).

In this framework, any increase in risk aversion sets off a raise in all risk premia, and therefore simultaneous a fall in asset prices across all financial markets. If this occurs suddenly, this may prompt a financial crisis. The interesting feature about this theoretical decomposition is that the financial crisis may burst even if the “quantity of risk” included in the assets has not changed.

* Corresponding author. Banque de France, DGO, DCSF, 31, rue, Croix des Petits champs, 75001 Paris, France. Tel.: +33 1 42 92 48 51; fax: +33 1 42 92 48 67.

E-mail addresses: virginie.coudert@banque-france.fr (V. Coudert), mathieu.gex@banque-france.fr (M. Gex).

Despite the readiness of its theoretical definition, risk aversion raises thorny issues when it comes to empirical matters, as it is not directly observable. Distinguishing the risk perceived by agents from risk aversion itself is very delicate. Several methods have been developed to assess risk aversion, especially by financial institutions. Disappointingly, they yield empirical indicators, which often show different trends. We try here to review them and assess their respective relevance. For doing this, we rely on a criterion derived from their theoretical properties: we assume that a “good” risk aversion indicator should significantly increase before financial market crises. This criterion allows us to discriminate the helpful empirical indicators.

The main aversion indicators which are commonly used by financial institutions can be grouped in different types: the *Global Risk Aversion Indexes*, the “GRAIs”, introduced by Kumar and Persaud (2002), based on the correlation between volatilities and changes in assets’ prices; indicators using a principal components analysis (PCA) on risk premia, as constructed by Sløk and Kennedy (2004); the *Volatility Index*, the “VIX”, using implicit volatility of option prices, created by the Chicago Board Options Exchange (CBOE, 2004); the *Liquidity, Credit and Volatility Index*, the “LCVI”, a synthetic indicator constructed by J.P. Morgan (Prat-Gay and McCormick, 1999; 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.

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 (Kamnisky et al., 1997; Berg and Pattilo, 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 et al., 1996; Radelet and Sachs, 1998). 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, in order to test their impact on financial crises.

The rest of the paper is organized as follows. 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 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, two periods of time, 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. A further assumption is that the agent can buy and sell freely this asset without transaction costs.

$$\begin{cases} \max_{\{\xi\}} u(c_t) + E_t[\delta u(c_{t+1})] \\ c_t = y_t - p_t \xi \\ c_{t+1} = y_{t+1} + x_{t+1} \xi \end{cases} \quad (1)$$

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:

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

The asset price expressed in Eq. (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):

$$p_t = E_t(m_{t+1} x_{t+1}) \quad (3)$$

with

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

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:

$$1 = E(m_{t+1} R_{t+1}) \quad (5)$$

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_{t+1}^f , is known in advance:

$$R_{t+1}^f = \frac{1}{E(m_{t+1})} \quad (6)$$

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

Considering Eqs. (5) and (6), we have:

$$E(R_{t+1}) - R_{t+1}^f = -\text{cov}(m_{t+1}, R_{t+1}) R_{t+1}^f \quad (7)$$

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:

$$E(R_{t+1}) - R_{t+1}^f = \left(-\frac{\text{cov}(R_{t+1}, m_{t+1})}{\text{var}(m_{t+1})} \right) \left(\frac{\text{var}(m_{t+1})}{E(m_{t+1})} \right) \quad (8)$$

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

$$E(R_{t+1}^i) - R_{t+1}^f = \left(-\frac{\text{cov}(R_{t+1}^i, m_{t+1})}{\text{var}(m_{t+1})} \right) \left(\frac{\text{var}(m_{t+1})}{E(m_{t+1})} \right) \quad (9)$$

which can be written in the form:

$$E(R_{t+1}^i) - R_{t+1}^f = \beta_{i,m} \lambda_m \quad (10)$$

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

with

$$\beta_{i,m} = -\frac{\text{cov}(R_{t+1}^i, m_{t+1})}{\text{var}(m_{t+1})} \quad (11)$$

and

$$\lambda_m = \frac{\text{var}(m_{t+1})}{E(m_{t+1})} \quad (12)$$

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:

$$m_{t+1} = \delta(c_{t+1}/c_t)^{-\gamma}. \quad (13)$$

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

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

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 \(1965a,b\)](#) 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:

$$m_{t+1} = a - bR_{t+1}^W \quad (15)$$

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:

$$R_{t+1}^m = \sum_i \alpha_i R_{t+1}^i \quad (16)$$

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:

$$m_{t+1} = a - bR_{t+1}^m \quad (17)$$

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

$$E(R_{t+1}^i) = R_{t+1}^f - R_{t+1}^f \text{cov}(R_{t+1}^i, a - bR_{t+1}^m) = R_{t+1}^f + R_{t+1}^f b \text{cov}(R_{t+1}^i, R_{t+1}^m) \quad (18)$$

² The theoretical values of these parameters are obtained by setting: $1 = E_t(m_{t+1} R_{t+1}^W)$ et $1 = E_t(m_{t+1}) R_{t+1}^f$.

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

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

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

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

with

$$\beta_{i,m} = \frac{\text{cov}(R_{t+1}^i, R_{t+1}^m)}{\text{var}(R_{t+1}^m)} \quad (21)$$

$$\lambda_m = b \frac{\text{var}(R_{t+1}^m)}{E(R_{t+1}^m)} \quad (22)$$

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.

$$m_{t+1} = f_{t+1}' b \quad (23)$$

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 an increase in risk premia across all markets, but the increase should be greater on the riskiest markets. This is the idea on which the 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 Eqs. (20)–(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).

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

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

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

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 Eq. (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:

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

Eq. (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:

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

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

$$\frac{\partial[P_t]}{\partial\lambda} = -\frac{\alpha_i\sigma_i^2}{\sigma_m^2} \quad (28)$$

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 et al. \(2004\)](#).

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. Others like [Crédit Suisse First Boston \(Wilmot et al., 2004\)](#) 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 ([Misina, 2003, 2006](#)). Especially, if the assumption of independence of excess returns is dropped, the change in risk premium due to risk aversion is no more proportional to the asset volatility (as it is the case in Eq. (25)), which means that the GRAI does not correctly measure risk aversion changes. 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.

Here, we calculate a GRAI and a RAI for the foreign exchange and stock markets using monthly data over the period from January 1995 to September 2005. For both, volatility is calculated over the two previous years. For the currency GRAI, the sample comprises 15 exchange rates against the USD; 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 (for more details, see Appendix A).

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” $f_1, \dots, f_p$ ($p \leq n$) 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; 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 ($\rho = -0.69$). 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 themselves from the risk of price fluctuations. The 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; Kantor and Caglayan, 2002), UBS’s Risk Index (Germanier, 2003), Merrill Lynch’s Financial

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.

Table 1

Cross-correlations of risk aversion indicators

	Stock market GRAI	Currency RAI	Stock market RAI	PCA	VIX	LCVI	ICI
Currency GRAI	0.09	0.85***	0.07	0.07	−0.18**	0.09	−0.07
Stock market GRAI		0.17*	0.85***	0.53***	0.24***	0.35***	−0.12
Currency RAI			0.13	0.14	−0.14	0.14	−0.11
Stock market RAI				0.40***	0.15*	0.25**	−0.19*
PCA					0.83***	0.51***	−0.39***
VIX						0.56***	−0.20*
LCVI							0.03

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

Stress Index (Rosenberg, 2003) and the Risk Perception Indicator of the *Caisse des Dépôts et Consignations* (Tampereau and Teiletche, 2001).

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, 2006). 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; 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 B, 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 rise in risk aversion.⁴ However, the GRAI and RAI do not display any very clear trend. During the stock

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

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 20 out of 28 of these correlations are positive (Table 1). Of the seven remaining, only four are significantly different from zero.

4. Methodology used to assess the link between risk aversion indicators and crises

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 A.

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 et al., 1996; Kamnisky et al., 1997; Corsetti et al., 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, $r_{i,t}$.

$$\begin{aligned} C'_{i,t} &= \alpha_{i,t} e_{i,t} + (1 - \alpha_{i,t}) r_{i,t} \\ \alpha_{i,t} &= 1/\text{var}_t(e_{i,t})/[1/\text{var}_t(e_{i,t}) + 1/\text{var}_t(r_{i,t})] \end{aligned} \quad (29)$$

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

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

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.

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:

$$\text{CMAX}_{i,t} = \frac{P_{i,t}}{\max(P_{i,t}, \dots, P_{i,t-24})} \quad (31)$$

This indicator equals 1 when $P_{i,t} = \max(P_{i,t}, \dots, P_{i,t-24})$. This is the case when that is a monotonous upward trend during the preceding 2 years. The more prices fall, the closer $\text{CMAX}_{i,t}$ gets to 0. Here again, to define crises, a threshold is used to identify periods when $\text{CMAX}_{i,t}$ 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. The stock market crisis indicator $C_{i,t}^{\text{Stock}}$ is defined as following:

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

In order to have a sufficiently large sample, the mean $\text{CMAX}_{i,t}$ 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 33 crises in the sample, i.e. an average of 1.2 crises per country. Almost all of them occur during the stock market fall in the early 2000s.

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 in the regressions

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

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).

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:

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

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.

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

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:

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

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 by adding a risk aversion indicator λ_t among the explanatory variables:

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

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:

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

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.⁷

For currency crises, most studies use the same explanatory variables in their model (for an exhaustive list, see [Berg and Pattilo, 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

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

⁷ Due to lack of space, only the main conclusions of the multilogit models are presented here. Detailed results are available upon request.

Table 2

Logit estimates, currency crises, Models (1) and (2)

	Estimation period: 07/1995–09/2005				Estimation period: 12/1998–09/2005			
	Number of observations=2186				Number of observations=1521			
	Base	Model (2)	Model (2)	Model (2)	Base	Model (2)	Model (2)	Model (2)
	Model (1)	GRAI	RAI	VIX	Model (1)	PCA	LCVI	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.

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 give the estimated probabilities of a crisis within one year. In order to obtain genuine crisis “predictions”, the models should be estimated over a given period, then simulated out-of-sample. Here, the problem in using out-of-sample simulations is that there are hardly no crises at the end of our sample (from 2003 on), so forecasting on the latter period would be fallacious, as we could not know the ratio of crises correctly predicted by our models. Moreover, as the sample is already small, splitting it would weaken the reliability of the estimates. In addition, Inoue and Kilian (2005) showed that in-sample tests could be more powerful than out-of-sample tests, when using small samples. For all these reasons, we prefer to present the in-sample simulations.

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. Regression results for 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 2).⁸ 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).

⁸ To compare the results of the three models, the estimation sample must be identical. However, some of our indicators (LCVI, PCA and ICI) start later (in December 1998) than the others (GRAI, RAI and VIX, in July 1995). In order to keep the information about the 1997 crises as far as possible, we present the results of all three models for GRAI, RAI, VIX, on a sample starting in July 1995 and for LCVI, PCA and ICI on a sample starting in December 1998.

Table 3

Logit estimates, currency crises, Model (3)

	Estimation period: 07/1995–09/2005			Estimation period: 12/1998–09/2005		
	Number of observations = 2186			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 R^2	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 2.

n.a.: no crisis predicted by the model.

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 2 and 3).

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)). 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 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 3). Results are not very different

Table 4

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

	Estimation period: 12/1998–09/2005						
	Number of observations = 1918						
	Base Model (1)	Model (2) GRAI	Model (2) RAI	Model (2) VIX	Model (2) PCA	Model (2) LCVI	Model (2) ICI
Constant	–2.70***	–2.73***	–2.59***	–4.02***	–3.19***	–2.52***	–5.29***
PER	0.38***	0.43***	0.40***	0.39***	0.38***	0.37***	0.38***
Returns	–2.14***	–2.03***	–2.04**	–1.90***	–1.58***	–2.14***	–2.08***
Real interest rate	–0.35***	–0.43***	–0.41***	–0.41***	–0.53***	–0.33***	–0.36***
Risk aversion indicator		1.44***	0.69***	0.06***	0.56***	0.00	–0.03**
Log likelihood	–592.8	–573.7	–570.7	–583.4	–518.8	–592.4	–589.6
Pseudo R^2	0.31	0.33	0.33	0.32	0.39	0.31	0.31
Correctly predicted crises ^a	80.8%	82.3%	80.5%	81.1%	86.2%	84.1%	81.4%
False alarms ^b	51.4%	49.8%	50.0%	51.8%	49.9%	51.3%	50.8%

Notes: see Table 2.

Table 5

Logit estimates, stock market crises, Model (3)

	Estimation period: 12/1998–09/2005					
	Number of observations=1918					
	GRAI	RAI	VIX	PCA	LCVI	ICI
Constant	−1.62***	−1.48***	−5.01***	−2.36***	−1.49***	−6.79***
Risk aversion indicator	1.89***	0.98***	0.15***	0.70***	0.00	−0.05***
Log likelihood	−834.5	−829.0	−785.0	−671.2	−886.8	−862.9
Pseudo R^2	0.05	0.06	0.11	0.23	0.00	0.03
Correctly predicted crises ^a	64.1%	69.2%	46.7%	79.6%	0%	36.2%
False alarms ^b	71.2%	70.2%	76.5%	59.3%	n.a.	78.7%

Notes: see Table 2.

n.a.: no crisis predicted by the model.

with multilogit models. Here, the indicators PCA and LCVI improve the predictive power of the model by 4% on the reduced period.

6. Regression results for stock market crises

6.1. Significance of the control variables and the risk aversion indicators

All of the explanatory variables introduced into the base Model of stock market crises are significant (Table 4).⁹ 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 4) or when taken alone (Table 5). Here again, the only exceptions are the ICI, which is negative, and the LCVI, which is not significant.

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

6.2. Predictive power for stock market crises

The base Model predicts 81% of stock market crises, with a false alarm ratio of 51%. Added into a regression with the control variables, the risk aversion indicators slightly increase these good results in terms of prediction (Table 4). 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 80% of crises correctly predicted and 59% of false alarms, then come the RAI and the GRAI (with 69% to 64% of crises correctly predicted and around 70% of false alarms) (Table 5). As for currency crises, multilogit models do not improve these forecasts.

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: for example 87% of correctly predicted crises, versus 86% with the PCA in Model (2); 79% versus 80% 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.

⁹ 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 most 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.

Table 6

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

	Estimation period: 12/1998–09/2005						
	Number of observations = 1959						
	Base	Model (2)	Model (2)	Model (2)	Model (2)	Model (2)	Model (2)
	Model (1)	GRAI	RAI	VIX	PCA	LCVI	ICI
Constant	−1.83***	−1.76***	−1.72***	−4.80***	−2.11***	−4.52***	−7.10***
PER	0.19***	0.19***	0.29***	0.06	−0.02	0.15**	0.17***
Returns	0.77***	0.85**	0.79***	1.02***	1.24***	0.82***	0.80***
Real interest rate	0.50***	0.45***	0.47***	0.33***	0.22***	0.16*	0.46***
Risk aversion indicator		1.50***	0.38***	0.13***	0.59***	0.06***	−0.06***
Log likelihood	−736.3	−712.2	−728.2	−681.8	−613.4	−652.4	−717.4
Pseudo R ²	0.10	0.13	0.12	0.16	0.23	0.19	0.12
Correctly predicted crises ^a	50.0%	53.0%	49.3%	60.7%	69.5%	66.1%	52.4%
False alarms ^b	66.6%	66.0%	68.0%	60.9%	55.4%	60.3%	65.0%

Notes: see Table 2.

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:

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

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 6). The risk aversion indicators are significant and positive in Model (2) and (3), except the ICI (Tables 6 and 7). 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

Table 7

Logit estimates, stock market reversals, Model (3)

	Estimation period: 12/1998–09/2005					
	Number of observations=1959					
	GRAI	RAI	VIX	PCA	LCVI	ICI
Constant	−1.66***	−1.63***	−3.17***	−1.87***	−4.20***	−6.37***
Risk aversion indicator	1.14***	0.31***	0.07***	0.31***	0.05***	−0.05***
Log likelihood	−818.8	−828.6	−814.3	−776.2	−734.6	−819.2
Pseudo R^2	0.02	0.01	0.02	0.06	0.10	0.02
Correctly predicted crises ^a	27.2%	0%	6.0%	35.6%	45.6%	23.2%
False alarms ^b	72.8%	n.a.	94.7%	79.8%	71.8%	76.9%

Notes: see Table 2.

n.a.: no crisis predicted by the model.

ICI. 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 spans a certain amount of time.

Model (1) allows to predict 50% of the reversals, with a false alarms ratio of 67%. Some of the risk aversion indicators improve the forecasts, notably the PCA and the LCVI (70% and 66% of correctly predicted crises) (Table 6). When used alone, the best performances in reversals detection are also obtained by the PCA and the LCVI (36% and 46%). On the other hand, the VIX and the RAI's predictive power are null (Table 7). The false alarms ratio remains high for all the indicators (more than 70%). The multilogit models do not improve significantly these forecasts. 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.

Appendix A. The database

A.1. The currency GRAI

Exchange rates against USD according for the following countries: Australia, Canada, Czech Republic, Germany then euro area from 1999, Hong Kong, Japan, Mexico, New Zealand, Norway, Poland, South Africa, Sweden, Switzerland and the United Kingdom. Source: Bloomberg. For Czech Republic, Mexico and Poland, data for 3-month forward rates start respectively from Dec 1996, Nov 1997 and July 1998. The currency RAI is made up of the same sample, except these 3 countries, as a different number of series over time would produce abrupt changes in the regression slope.

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. Source: Bloomberg.

A.2. Components of the PCA

8 risk premia are used: 4 corporate bond spreads for the euro area and the United States: 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 Emerging Markets Bond Index Global (EMBI Global) (an index calculated by J.P. Morgan since mid-1998 that represents the average price of sovereign dollar-denominated bonds issued by emerging countries) and second, an index of corporate debt, denominated in dollars or euros and issued abroad, of a large number of emerging market countries, calculated by the bank Merrill Lynch; 2 swap spreads, one for the euro area and one for the United States. Source: Bloomberg.

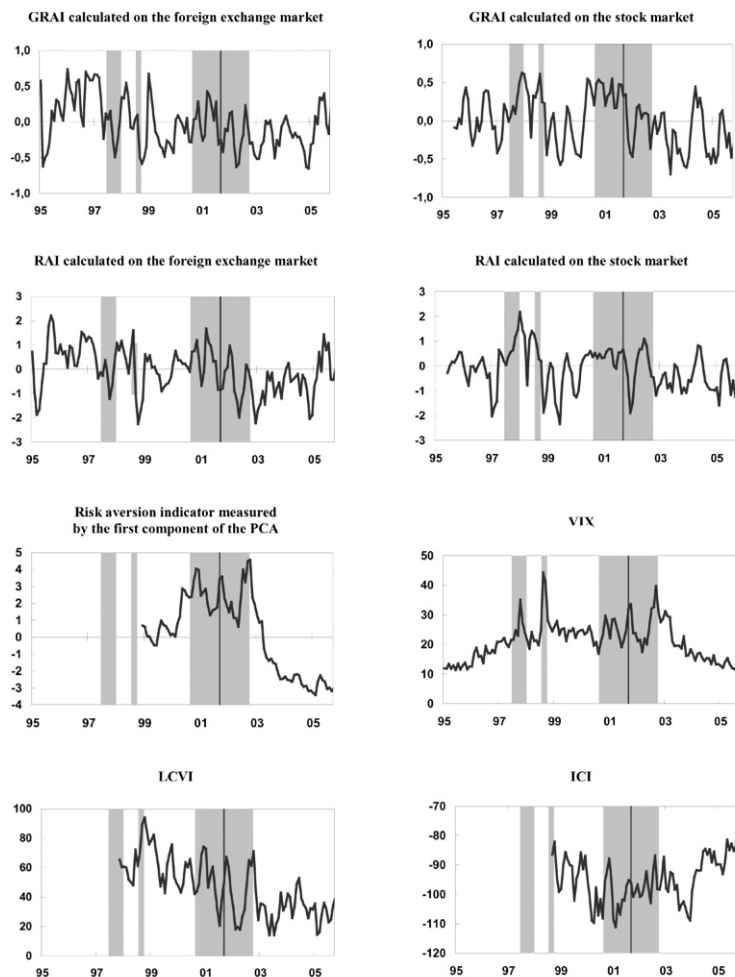
A.3. Crisis indicators

Currency crisis: 20 countries: Argentina, Brazil, Bulgaria, Chile, Colombia, Czech Republic, Estonia, Hungary, Indonesia, Latvia, Lithuania, Mexico, Philippines, Poland, Romania, Singapore, South Korea, Thailand, Uruguay and

Venezuela. Source: IMF's International Financial Statistics (IFS). To obtain the reserves/M2 ratio: total reserves minus gold, line 1 l.d., money, line 34, quasi-money, line 35; to calculate the real exchange rates: line ae, consumer prices index (CPI), line 64; to calculate the real interest rates: money market rates, lines 60, 60b or 60a (depending on the availability of data and in this order of preference), and CPI. When monthly data were not available, we made linear interpolation using quarterly data.

Stock market crisis: same 27 countries as for the GRAI, and same stock market indexes. The returns have been calculated as year-on-year increase in each stock market index. The PER have 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 B. Risk aversion indicators graphs



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.

References

- Ades, A., Fuentes, M., 2003. Risk aversion. Goldman Sachs Foreign Exchange Market 28–31 (October).
- Back, 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*, vol. 46-2.
- Bliss, R., Panigirtzoglou, N., 2004. Option-implied risk aversion estimates. *Journal of Finance* 59 (1), 407–446.

- 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, vol. 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, vol. 6783.
- Deutsche Bundesbank, 2004. Indicators of international investors' risk aversion. *Monthly Report*, vol. 56-10, pp. 69–73.
- Deutsche Bundesbank, 2005. Risk appetite in a dynamical financial market environment. *Monthly Report*, vol. 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, vol. 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, vol. 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.
- Inoue, A., Kilian, L., 2005. In-sample or out-of-sample tests of predictability: which one should we use? *Econometric Reviews* 23 (4), 371–402.
- Kaminsky, G., Lizondo, S., Reinhart, C., 1997. Leading indicators of currency crises. IMF Working Paper, vol. 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, vol. 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.
- 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*, pp. 65–78. December.
- Mishkin, F., White, E., 2002. US stock market crashes and their aftermath: implications for monetary policy. NBER Working Paper, vol. 8992.
- Misina, M., 2003. What does the risk-appetite index measure? Bank of Canada Working Paper, vol. 2003-23.
- Misina, M., 2006. Benchmark index of risk appetite. Bank of Canada Working Paper, vol. 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*, fourth edition. McGraw-Hill, 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*, pp. 4–10. June.
- 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*, vol. 27, 1, pp. 147–199.
- Scheicher, M., 2003. What drives investor risk aversion? Daily evidence from the German equity market. *BIS Quarterly Bulletin*, pp. 69–77. June.
- 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, vol. 385.
- Tampereau, Y., Teiletche, J., 2001. Comment mesurer l'aversion pour le risque ? Note Flash, vol. 2001-155. CDC Ixis Capital Markets.
- Tarashev, N., Tsatsaronis, K., Karampatos, D., 2003. Investors' attitude towards risk: what can we learn from options? *BIS Quarterly Bulletin*, pp. 59–68. June.
- 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.