Can risk aversion indicators anticipate financial crises?

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Fluctuations in investor risk aversion are often cited as a factor explaining crises on financial markets. The alternation between periods of bullishness prompting investors to make risky investments, and periods of bearishness, when they retreat to the safest forms of investments, could be at the root of sharp fluctuations in asset prices. One problem in the assessment of these different periods is clearly distinguishing the risk perceived by agents from risk aversion itself.

There are several types of risk aversion indicators used by financial institutions (the VIX, the LCVI, the GRAI, etc.). These indices, which are estimated in diverse ways, often show differing developments, although it is not possible to directly assess which is the most accurate. An interesting method in this respect is to link the indicators to financial crises. In principle, financial crises should coincide with periods in which risk aversion increases. Here we estimate probabilities of financial crises –currency and stock market crises– using the different risk aversion indicators as explanatory variables. This allows us to assess their respective predictive powers. The tests carried out show that risk aversion does tend to increase before crises, at least when it is measured by the most relevant indices. This variable is a good leading indicator of stock market crises, but is less so for currency crises.

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. One problem in the assessment of these different periods is clearly distinguishing the risk perceived by agents from risk aversion itself.

The concept of risk aversion has the advantage of being intuitive, given that it can easily be interpreted as a feeling of wariness on the part of investors regarding risky investments. It can also be defined more precisely within the framework of asset pricing models. In this context, we can decompose risk premia on different assets into a "price of risk", which is common to all assets, and a "quantity of risk", which is specific to each asset. Risk aversion is often considered to correspond to the "price of risk" obtained in this way. This is the definition we use here.

In the consumption capital asset pricing model (CCAPM), the price of risk depends on the variance of consumption. It may therefore vary empirically if this variance is estimated over different periods. In the specific case of the capital asset pricing model (CAPM), the price of risk varies with the variance of returns on a representative market portfolio (see Appendix 1).

There seems to be a paradox in regarding risk aversion as being variable over time when it is defined as a structural factor representing agents' preferences. In fact, this paradox stems from the dual use of the term "risk aversion".

• In its narrow sense, the term refers to the risk aversion coefficient present in the consumer's utility function. This parameter is part of the intrinsic profile of economic agents and may therefore be assumed to be unchanged over time.

• In its broad sense –which is the one used here– risk aversion is defined as the "price of risk". It is a decisive factor in the formation of asset prices, and makes it possible to reflect investor sentiment with regard to risk in an ever-changing environment. Another advantage of this definition is that it constitutes the opposite of the concept of "risk appetite" frequently mentioned by market operators.[1]

There are several types of risk aversion indicators in the economic literature. These indicators, which are estimated in diverse ways, often show differing developments, although it is not possible to directly assess which is the most accurate. An interesting method in this respect is to link the indicators to financial crises since, in principle, financial crises should be preceded by periods in which risk aversion increases. However, it is also possible for some financial crises to be preceded by periods of strong "risk appetite" during which investors are excessively optimistic, which creates a "speculative bubble" on the prices of risky assets.

The first part of this article describes the indicators most commonly used by financial institutions and compares their values over the period July 1995 to September 2005. The second part estimates probabilities of financial crises –currency and stock market crises– using these different indicators. The simulations carried out on the sample allow us to assess their respective predictive powers.

1| THE MAIN RISK AVERSION INDICATORS

1|1 Simple and aggregate indicators

SIMPLE INDICATORS, THE VIX

Some analyses use raw series to estimate changes in investors' perception of risk. For instance, the price of gold may be used if we assume that, during periods of uncertainty, investors will reallocate their wealth to assets traditionally perceived as safe, such as gold. The same would be true of the Swiss franc exchange rate.

The implied volatility of options is also used. For example, the volatility index (VIX) created

1 See Kumar and Persaud (2001), Gai and Vause (2004).

by the Chicago Board Options Exchange (CBOE) in 1993 equals the implied volatility on the S&P 500 (Chart 1). It is regarded by many market analysts as a direct gauge of fear.

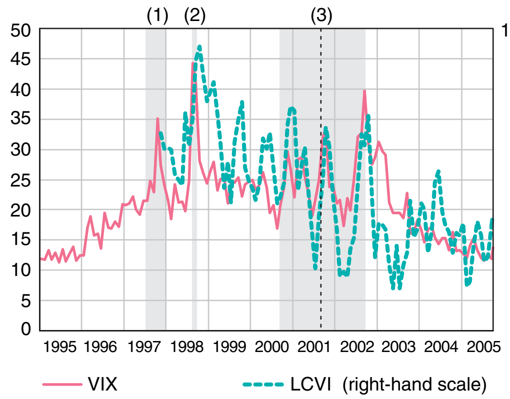
However, the explanatory power of these indicators is limited. Indeed, proxies like the price of gold may be influenced by factors that have nothing to do with risk aversion. Similarly, a variation in implied volatility on a market may stem from a change in the quantity of risk on this market and not necessarily from a change in investor risk aversion.

AGGREGATE INDICATORS, THE LCVI

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 JP Morgan's liquidity, credit and volatility index (LCVI), the UBS (Union des Banques Suisses) risk index, Merrill Lynch's financial stress index and the risk perception indicator of the Caisse des Dépôts et Consignations.[2]

We have used the LCVI in our comparison (see Chart 1). This is often regarded as being a satisfactory measure

Chart 1
VIX and LCVI
(level of VIX) *(level of LCVI; min = 0, max = 100)*



(1) Asian crisis.
(2) Russian crisis and failure of LTCM.
(3) Downtrend on the main stock markets.
Dotted line: terrorist attacks of 11 September 2001.
Sources: CBOE, JP Morgan.

of risk aversion.[3] 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).

However, these aggregate indicators are limited in their power to explain risk perception. 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. Moreover, the weighting of the different measures used is arbitrary. All in all, this approach appears based on intuition and lacks a real theoretical basis.

1|2 A common factor driving risk premia

Principal component analysis (PCA) may be applied to risk premia in order to identify a common factor in their variations (see Box 1). The assumption underlying this approach is that the yields on different securities are correlated as they depend on one or more common factors that are not directly observable.

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.

Here, we construct an indicator of this type, referred to hereafter as PCA, using the first component of a PCA on several risk premia (see Box 1). The risk premia 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

2 *For more details on these indicators see Prat-Gay and McCormick (1999), Kantor and Caglayan (2002), Germanier (2003), Rosenberg (2003), and Tampereau and Teiletche (2001).*
3 Dungey et al. *(2003), for example, use it to study changes in risk aversion during the financial crises in emerging markets.*

Box 1

Principles of principal component analysis

This approach is justified by Ross's arbitrage pricing theory (APT, 1976). According to this theory, the common variation in returns can be expressed as a linear function of a set of factors. However, APT specifies neither their number nor their nature. This leads to the use of statistical methods, such as principal component analysis (PCA), to identify them.

PCA allows us to extract from a set of p *quantitative variables correlated among one another a list of* k *new variables called "factors"* $f_1, \ldots, f_k$ $(k \leq p)$ *that are uncorrelated among one another. The common factors are constructed as linear combinations of 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.*

Examples of use

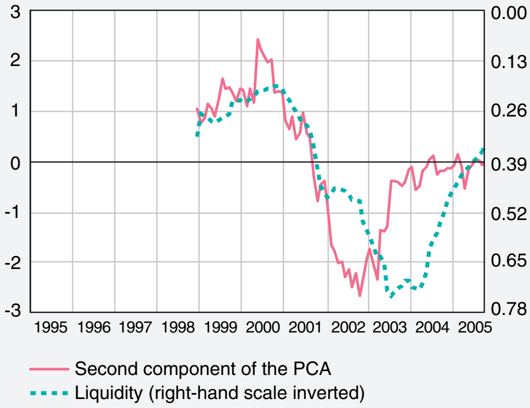
Sløk and Kennedy (2004) use PCA to identify a common trend in risk premia on stock and bond markets in developed and emerging market countries since the beginning of 1998. According to them, the variance-explained weighted average of the first two common factors is strongly correlated with the OECD's 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 in the period 1997 to 2003. 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.

Calculation of a PCA indicator on risk premia

The method used here is PCA carried out using a set of standardised risk premia (see Appendix 3). 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.

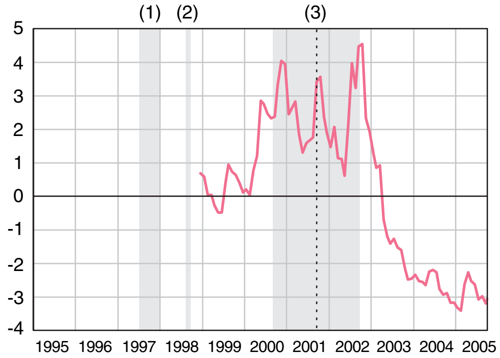
The second factor explains 19% of the common variation of risk premia. We analyse it since it satisfies the Joliffe criterion, at the 80% threshold, and the Kaiser criterion. This second factor is negatively correlated with a measure of global liquidity. This is proxied here by the inverse of average short-term rates of the four largest economies (United States, euro area, United Kingdom and Japan), weighted by GDP (the correlation coefficient is equal to -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.

Second component of the PCA compared with a measure of global liquidity



Sources: Bloomberg, JP Morgan, Merrill Lynch, OECD.

Chart 2
Risk aversion indicator measured by the first component of the PCA



(1) Asian crisis.
(2) Russian crisis and failure of LTCM.
(3) Downtrend on the main stock markets.
Dotted line: terrorist attacks of 11 September 2001.
Sources: Bloomberg, JP Morgan, Merrill Lynch.

and swap spreads for the major developed markets; on the other, the EMBI Global sovereign spread and a corporate spread for emerging market economies.[4] Details of these series are given in Appendix 3. The estimation period is from December 1998, when the indices used for emerging market countries were introduced, to December 2005 (Chart 2).

1|3 Indicators of the GRAI type

PRINCIPLES OF CALCULATION

Theoretically, 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 global risk aversion index (GRAI) is based, devised by Persaud (1996). Changes in risk aversion are represented by the correlation between price variations of different securities and their volatility: if the correlation is positive, risk aversion has decreased; if the correlation is negative, it has increased (for a more detailed presentation, see Appendix 2).

In practice, if we wish the GRAI to increase with risk aversion, the correlation must be given a negative sign.[5] 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).[6]

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.[7] However, it must be admitted that these confidence intervals are not calculated for other risk aversion indicators.

Kumar and Persaud (2001) applied this approach to *ex post* excess returns on foreign exchange markets. Several financial institutions and private banks, such as the IMF and JP Morgan, subsequently constructed their own GRAI. Others like Credit Suisse First Boston[8] and the Deutsche Bundesbank have constructed RAIs.

LIMITATIONS OF ITS USE

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. Another limitation of this indicator is that it does not measure levels of risk aversion but rather changes in it. The correlation coefficient only makes it possible to distinguish periods in which risk aversion has increased from those in which it has fallen.

From an empirical point of view, the GRAI and RAI also display some limitations. Firstly, the measurements show that these indicators are extremely volatile. This seems counter-intuitive, as a good indicator should be stable during quiet periods. Secondly, 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.

4 *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.*
5 *Spearman's correlation is often used, which is a correlation between ranks of variables.*
6 *See Wilmot, Mielczarski and Sweeney (2004).*
7 *More than half of the values in Kumar and Persaud's study (2001).*
8 *See Wilmot, Mielczarski and Sweeney (2004).*

CALCULATION OF A CURRENCY AND STOCK MARKET GRAI

We calculate the GRAI and RAI for the foreign exchange and stock markets using monthly data. The currency GRAI is equal to the correlation (which is given a negative sign) between excess returns and volatility (see Chart 3). The sample comprises 12 to 15 currencies quoted against the US dollar depending on the periods for which data are available (Appendix 3). Excess returns are equal to the spread between the 3-month forward rate and the actual spot rate three months later. Volatility is calculated over the two previous years.

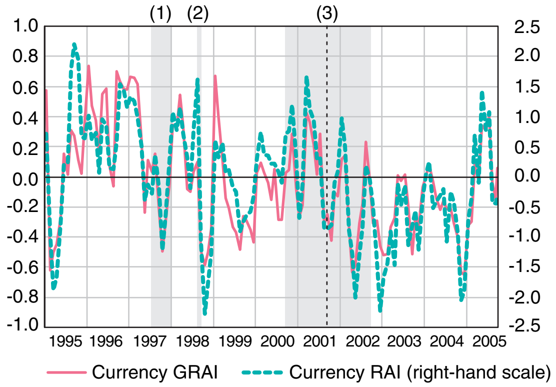
The stock market GRAI is equal to the correlation (given a negative sign) between price changes over three months and their volatilities, calculated over the two previous years (Chart 4). The sample is made up of the main stock market indices of 27 developed and emerging economies. The currency and stock market RAIs are calculated in the same way as the GRAIs, by replacing the rank correlation by the regression slope.

STATE STREET INDEX

The State Street index (SST) is based on a measure in volume terms rather than prices.[9] This index, which was created in 1998, can be regarded as a GRAI calculated in terms of quantity. 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.

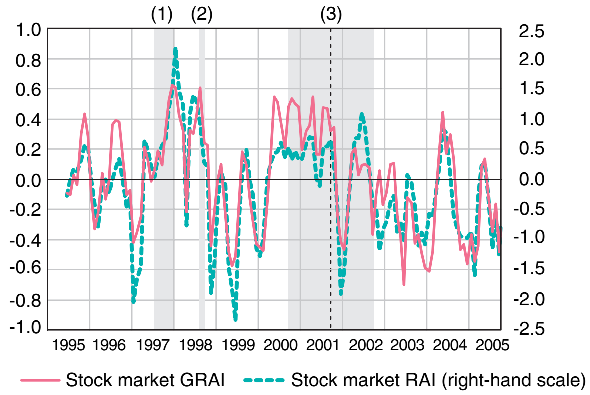
The index is calculated every month using State Street's proprietary database on the portfolios of institutional investors (see Chart 5). Like the other indicators in this category, this tool has the

Chart 3
GRAI and RAI calculated on the foreign exchange market



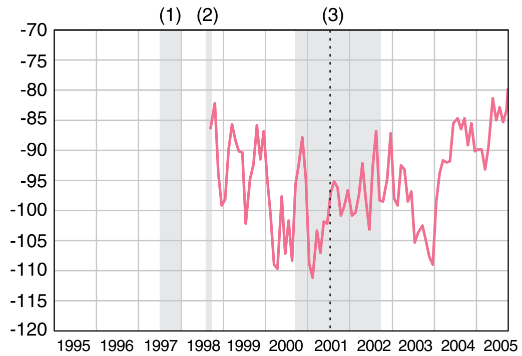
(1) Asian crisis.
(2) Russian crisis and failure of LTCM.
(3) Downtrend on the main stock markets.
Dotted line: terrorist attacks of 11 September 2001.
Source: Bloomberg.

Chart 4
GRAI and RAI calculated on the stock market



(1) Asian crisis.
(2) Russian crisis and failure of LTCM.
(3) Downtrend on the main stock markets.
Dotted line: terrorist attacks of 11 September 2001.
Source: Bloomberg.

Chart 5
State Street index (given a negative sign)



(1) Asian crisis.
(2) Russian crisis and failure of LTCM.
(3) Downtrend on the main stock markets.
Dotted line: terrorist attacks of 11 September 2001.
Source: State Street.

9 *See Froot and O'Connell (2003).*

advantage of being simple and can provide useful indices; however, it shows up trends that are not solely a reflection of risk aversion.

1|4 Other measures

Another category of indicators is obtained by comparing risk-neutral probabilities, calculated on options prices, with investors' subjective probabilities. We have not used this type of indicator here as it is tricky to estimate empirically subjective probabilities using historical data.[10] 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.[11] Indeed, many studies have shown that consumption models underperform models that use market data such as the CAPM.

1|5 Comparison of the indicators

The different indicators react more or less to periods of crisis, identified in Charts 1 to 5 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.[12] 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 SST 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.

Table 1
Cross-correlations of risk aversion indicators

	Stock market GRAI	Currency RAI	Stock market RAI	PCA	VIX	LCVI	SST
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%, or *** 99% confidence levels.*

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 1). Of the seven remaining, only three are significantly different from zero.

2| PREDICTIVE POWER OF THE INDICATORS

We attempt here to determine whether the risk aversion indicators described above can serve as leading indicators of crises, and whether they can help to improve forecasts using existing models. 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.

Much work has been done to attempt to construct "leading indicators" of crises, notably after the Mexican crisis in 1995.[13] 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

10 See Tarashev et al. (2003), Scheicher (2003), Bliss and Panigirtzoglou (2004); for a survey, see Gai and Vause (2004).
11 See Ades and Fuentes (2003).
12 In the case of the LCVI, only the Russian crisis is concerned, as the series is only available from the end of 1997.
13 See for example Kaminsky, Lizondo and Reinhart (1997), Berg and Patillo (1999), or Bussière and Fratzscher (2002).

(crisis or quiet period) to a set of quantitative exogenous variables.[14] These models are estimated for a large number of countries and periods. We use the same method here.

2|1 The method used

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 (Box 2). Crisis periods are identified by so-called "simultaneous" indicators, which will be used to construct the model's dependent variable. Next, in order to assess the power of different risk aversion indicators to predict crises, they need to be compared with the indicators generally used.

EXPLANATORY VARIABLES

For currency crises, most studies use the same explanatory variables in their model.[15] 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 indirectly, 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 are the following:[16] the price earning ratio (PER) in level terms, the year-on-year change in stock prices, and real interest rates.[17]

The explanatory variables are then introduced into the model in several stages to see whether the risk aversion indicators improve forecasts (see Box 3). Three models are tested in turn. Model (1) is referred to as the "base" and includes the usual explanatory variables without the risk aversion indicators. Model (2) adds the different indicators in turn. Model (3) only includes a risk aversion indicator as explanatory variable.

SAMPLE USED

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 3.

The aim is to compare the results obtained with these three types of model. To do this, the estimation sample must be identical. However, as some of our indicators (LCVI, PCA and SST) 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.

2|2 Currency crises

The explanatory variables of currency crises have the expected signs (see Table 2). Appreciation of the real exchange rate is supposed to increase the risk of crisis, which corresponds to the negative sign found. A fall in international reserves relative to broad money also increases the probability of a crisis, hence the negative sign. 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.

The risk aversion variables all have the positive sign expected, with a rise in them contributing to increasing the probability of a crisis, except for the SST index. They appear very significant in regressions over the longer period. This is the case for the VIX, the GRAI and the RAI. In the estimates for the shorter period, only the PCA is significant at 99%.

14 *See Frankel and Rose (1996), Sachs, Tornell and Velasco (1996), or Radelet and Sachs (1998).*
15 *For an exhaustive list, see Berg and Patillo (1999).*
16 *Among those proposed by Boucher (2004).*
17 *All of these explanatory variables have been standardised for each country in order to obtain homogenous data for all countries.*

Box 2

Definition of crises

Currency crises

There is abundant literature on currency crises, which makes it possible to construct simultaneous crisis indicators. Most of them are obtained by statistical analysis of exchange rate and official international reserves series. The usual method consists in first of all constructing "pressure on the foreign exchange market" indicators, which correspond to a weighted average of the currency's depreciation and relative losses in international reserves (see, for example, Sachs, Tornell and Velasco, 1996, Kaminsky, Lizondo and Reinhart, 1997, Corsetti, Pesenti and Roubini, 1998, Bussière and Fratzscher, 2002). The weighting used between the two series is generally inversely proportional to their conditional variance. 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 calibrate the number of standard deviations, so that all of the crises detected coincide with known crises on the markets and vice versa.

The sample used is described in Appendix 3. The reference currency to measure depreciation is the dollar for all the currencies of Latin America and Asia, 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. 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 (inflation higher than 150% in the six preceding months) are given particular treatment; this is the case for Bulgaria and Romania in our sample. In this case, we divide the sample in two: 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.[1]

With a threshold set at three standard deviations above average, the indicator thus constructed allows us to identify only known currency crises –such as those in the Asian countries in the second half of 1997 or in Brazil in January 1999 and Argentina in January 2002. In total, 18 crises are detected, that is, an average 0.9 crisis per country.

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.[2] *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 (24 months, for example). This involves dividing the current price by the maximum price over the period: $\mathrm{CMAX}_t = \mathrm{P}_t / \max [\mathrm{P}_{t-24},\ldots,\mathrm{P}_t]$ *where* P_t *is the stock price at time* t. *This indicator equals 1 if prices rise over the period considered. The more prices fall, the closer it gets to 0. The threshold used is generally equal to the mean less two or three standard deviations. 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.*

Over our sample (see Appendix 3), by using a threshold of two standard deviations below the mean, we identify crises that correspond to recognised events over the period.[3] *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.*

1 *The average and standard deviation are calculated by dividing the sample for hyperinflation countries. At the start of the period, they are calculated on data from August 1993 to December 1997, then conditionally, by gradually adding a month to the sample. We add an extra criterion to avoid counting the same crisis several times: if a crisis is detected wihin a 12-month period following another crisis, it is automatically cancelled out.*
2 *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 this method lies in the practical determination of the fundamental value as well as the econometric identification of these bubbles (Boucher, 2004).*
3 *In order to have a sufficiently large sample, the mean and standard deviation are first calculated over ten years from March 1995 to March 2005, and then conditionally by gradually adding a 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.*

Box 3

Models used to predict crises

The dependent variable: creation of pre- and post-crisis windows

Using the crises defined above, we construct an indicator denoted $I_{i,t}$ composed solely of 0 and 1. It equals 1 for the 12 months preceding crises and the crisis itself; 0 in 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. 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. Using a misnomer, we refer to this indicator $I_{i,t}$ as a "crisis indicator".

Logit estimates

We carry out three types of estimate in turn. First, we estimate the base model, using the explanatory variables generally used to predict crises. This model is as follows:

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

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

Given the construction of our indicator $I_{i,t}$, this model directly estimates the probability of a crisis at a one-year horizon. Secondly, we estimate the same equation by adding a risk aversion indicator λ_t among the explanatory variables:

$$\Pr(I_{i,t} = 1) = f\left(\alpha_0 + \sum_{k=1}^{n}\alpha_k X_{i,t}^k + \alpha_{n+1}\lambda_t\right) \quad (2)$$

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

Thirdly, we estimate the same model with the risk aversion indicator as the only explanatory variable:

$$\Pr(I_{i,t} = 1) = f(\alpha_0 + \alpha_{n+1}\lambda_t)) \quad (3)$$

In order to be entirely rigorous, to obtain genuine crisis "predictions", we would have to estimate the models over given period, then simulate them "out-of-sample", that is, over a period subsequent to the estimates. Here we have estimated and simulated the probability of crises over the same period. The availability of our data is too limited to be able 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 this text, however, using a misnomer, we speak of the model's «predictive power» to refer to the adequacy of the values estimated by the model for the occurrence of crises within the sample.

The different models are then simulated over the sample period. The results give the estimated probabilities of a crisis. 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%.[18]

The first estimate for the period July 1995 to September 2005 gives much better results as far as the quality of forecasting is concerned. Sixty-one percent of crises are correctly predicted by the base model. In the second estimate, which starts in December 1998, the number of crisis periods

18 *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%). This threshold is not an intrinsic feature of the model; it merely serves to present the results. By setting it at a low level, as we do here, the probability estimated by the model has more chance of exceeding this threshold and therefore the number of crises predicted is greater. However, the number of "false alarms",* i.e. *the number of wrongly predicted crises also increases.*

Table 2
Logit estimates, currency crises
(estimation period: 07/1995 – 09/2005, number of observations = 2,186)

	Base model (1)	Model (2) VIX	Model (2) RAI	Model (2) GRAI
Constant	1.50 ***	1.17 ***	1.43 ***	0.29 ***
Real exchange rate	-4.47 ***	-5.21 ***	-4.42 ***	-4.26 ***
Reserves/M2	-0.96 ***	-0.97 ***	-0.92 ***	-0.92 ***
Real interest rate	1.19 ***	1.12 ***	1.21 ***	1.21 ***
Risk aversion indicator		0.05 ***	0.26 ***	0.86 ***
Log likelihood	-508.2	-502.9	-504.0	-501.4
Pseudo R²	0.16	0.17	0.17	0.17
Crises predicted correctly[a)]	61.2%	62.9%	62.5%	63.4%
False alarms[b)]	59.1%	57.8%	58.8%	57.6%

(estimation period: 12/1998 – 09/2005, number of observations = 1,521)

	Base model (1)	Model (2) LCVI	Model (2) PCA	Model (2) SST
Constant	-0.20	-0.07	2.03 **	-2.83 *
Real exchange rate	-2.93 ***	-2.86 ***	-5.43 ***	-3.35 ***
Reserves/M2	-0.89 ***	-0.91 ***	-0.93 ***	-0.93 ***
Real interest rate	1.76 ***	0.78 ***	0.60 ***	0.72 ***
Risk aversion indicator		0.00	0.34 ***	-0.03 *
Log likelihood	-289.6	-289.6	-249.1	-256.0
Pseudo R²	0.04	0.04	0.06	0.05
Crises predicted correctly[a)]	24.1%	24.1%	26.6%	26.6%
False alarms[b)]	65.5%	66.1%	61.1%	65.0%

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

Table 3
Logit estimates, model (3), currency crises
(estimation period: 07/1995 – 09/2005, number of observations = 2,255)

	VIX	GRAI	RAI
Constant	-2.80 ***	-2.20 ***	-2.20 ***
Risk aversion indicator	0.03 ***	1.11 ***	0.35 ***
Log likelihood	-647.2	-732.0	-736.9
Pseudo R²	0.00	0.01	0.01
Crises predicted correctly[a)]	0.0%	0.9%	0.0%
False alarms[b)]	na	88.9%	na

(estimation period: 12/1998 – 09/2005, number of observations = 1,543)

	LCVI	ACP	SST
Constant	-3.24 ***	-3.00 ***	-4.54 ***
Risk aversion indicator	0.00	0.15 ***	-0.02
Log likelihood	-311.1	-307.3	-311.1
Pseudo R²	0.00	0.01	0.00
Crises predicted correctly[a)]	0.0%	0.0%	0.0%
False alarms[b)]	na	na	na

*Significantly different from zero at the * 90%, ** 95%, *** and 99% confidence levels (Student's t).*
a) Number of crises predicted correctly as a % of total number of crises.
b) Number of crises wrongly predicted as a % of the number of crises predicted.
na: No crisis predicted by the model.

in the sample is considerably lower, with the Asian crises in 1997 notably disappearing from the sample. This leads to difficulty in estimating these crisis periods correctly. The ratio of correctly predicted crises then falls to 24%. The ratio of false alarms (number of false alarms relative to the total number of crises) for the two estimation periods is 59% and 66% respectively (see Table 2).

Introducing a risk aversion indicator makes it possible to improve the model's forecasts. This improvement is marginal when the model is estimated on the first period: the three indicators increase the ratio of correctly predicted crises by only 1%-2.5%, and reduce by only 1% the ratio of false alarms. By contrast, over the reduced period, given that the base model yields poor results, the improvement provided by the indicators is substantial, except in the case of the SST.

When they are introduced into the regressions, the risk aversion indicators are significant, except for the LCVI and the SST (see Table 3). However, their power to predict currency crises is nil.

2|3 Stock market crises

All of the explanatory variables introduced into the base model of stock market crises are significant (see Table 4).[19] 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 SST is the only exception.

19 *Unlike in the previous case, shortening the estimation period does not reduce the quality of the estimates or forecasts. 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.*

Table 4
Logit estimates, stock market crises

(estimation period 12/1998 – 09/2005, number of observations = 1,950)

	Base model (1)	Model (2) VIX	Model (2) GRAI	Model (2) RAI
Constant	-2.97 ***	-3.79 ***	-2.96 ***	-2.84 ***
PER	0.43 ***	0.42 ***	0.46 ***	0.44 ***
Returns	-2.33 ***	-2.18 ***	-2.22 ***	-2.22 **
Real interest rate	-0.20 **	-0.23 ***	-0.25 ***	-0.25 ***
Risk aversion indicator		0.04 ***	1.27 ***	0.60 ***
Log likelihood	-555.5	-552.1	-540.6	-538.8
Pseudo R²	0.33	0.34	0.35	0.35
Crises predicted correctly[a)]	84.4%	84.4%	86.0%	84.1%
False alarms[b)]	49.9%	48.8%	48.3%	48.1%

(estimation period 12/1998 – 09/2005, number of observations = 1,950)

	Modèle de base (1)	Modèle (2) LCVI	Modèle (2) ACP	Modèle (2) SST
Constant	-2.97 ***	-2.51 ***	-3.37 ***	-5.74 ***
PER	0.43 ***	0.41 ***	0.43 ***	0.42 ***
Returns	-2.33 ***	-2.36 ***	-1.80 ***	-2.28 ***
Real interest rate	-0.20 **	-0.16 *	-0.33 ***	-0.21 **
Risk aversion indicator		-0.01 **	0.53 ***	-0.03 ***
Log likelihood	-555.5	552.5	-497.0	-552.2
Pseudo R²	0.33	0.34	0.40	0.34
Crises predicted correctly[a)]	84.4%	84.8%	86.6%	84.4%
False alarms[b)]	49.9%	50.0%	48.5%	48.9%

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

Table 5
Logit estimates, Model (3), stock market crises

(estimation period: 12/1998 – 09/2005, number of observations = 1,950)

	VIX	GRAI	RAI
Constant	-4.86 ***	-1.66 ***	-1.54 ***
Risk aversion indicator	0.14 ***	1.78 ***	0.97 ***
Log likelihood	-784.4	-822.9	-816.0
Pseudo R²	0.09	0.05	0.06
Crises predicted correctly[a)]	43.3%	56.7%	66.4%
False alarms[b)]	77.5%	73.2%	70.6%

(estimation period: 12/1998 – 09/2005, number of observations = 1,950)

	LCVI	ACP	SST
Constant	-1.44 ***	-2.40 ***	-6.94 ***
Risk aversion indicator	-0.00	0.68 ***	-0.06 ***
Log likelihood	-871.4	-669.1	-848.2
Pseudo R²	0.01	0.21	0.02
Crises predicted correctly[a)]	0.0%	74.5%	26.5%
False alarms[b)]	na	61.9%	84.1%

*Significantly different from zero at the * 90%, ** 95%, *** and 99% confidence levels (Student's t).*
a) Number of crises predicted correctly as a % of total number of crises.
b) Number of crises wrongly predicted as a % of the number of crises predicted.
na: No crisis predicted by the model.

The base model predicts 84.4% of stock market crises, with a false alarm ratio of 49.9%. Added into a regression with the other explanatory variables, the risk aversion indicators lightly increase these good results in terms of prediction (Table 4). When they are taken alone, all the risk aversion indicators also obtain good results, with the exception of the LCVI (see Table 5). The GRAI and RAI have fairly similar predictive powers, with 56% to 67% of crises correctly predicted and around 70% of false alarms. The VIX and SST yield much less good results.

The interpretation of these good results should, however, be put in perspective, 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. Predicting turning points would be quite a different exercise.

On this basis, the PCA performs best, it being the only one to correctly predict 74.5% of the crises in the sample, with a false alarm ratio of 61.9%. How can the PCA's good performance, which is repeated when it is introduced alone in the regression (Table 5) or added to the other explanatory variables (Table 4), 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 variable in regressions (2) and (3) by the spreads themselves. The results (not detailed here due to lack of space) show that the eight spreads give estimates that are more or less equivalent to those obtained with the PCA. For Model (2), they succeed in predicting 88.2% of crises (compared to 86.6% for the PCA), with 44.7% false alarms (compared to 48.5% for the PCA). In Model (3), the eight spreads allow us to obtain a result of 76.3% of crises predicted correctly (compared to 74.5% for the PCA), with 50.6% false alarms (compared to 61.9% for the PCA). Overall, the predictions obtained with the PCA or the eight spreads together are more or less equivalent. Using a synthetic indicator such as the PCA is therefore preferable.

It appears then that risk aversion plays a part in stock market crises and that it is indeed captured by certain indicators. Their contribution is, however, small compared with the other explanatory factors.

Empirical risk aversion indicators are supposed to provide a synthetic indication of market sentiment with regard to risk. The tests conducted in this article show that risk aversion does indeed tend to increase before crises, at least when measured by the most relevant indicators. In other words, these indicators are significant in the regressions explaining the periods preceding financial crises. A rise in them also contributes to increasing the probability of a crisis. The fact that risk aversion is particularly high just before crises is consistent with the intuitive definition of this concept.

The predictive power of these indicators for currency crises is small. By contrast, in the case of stock market crises, most of the risk aversion indicators tested allow satisfactory results to be obtained. The best results regarding the prediction of stock market crises are obtained using principal component analysis on risk premia.

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APPENDIX 1

Theoretical framework

Review of a base model for asset prices: the CCAPM

We consider an investor who freely buys or sells an asset. To keep it simple, we assume that there is a single risky asset, two periods, constant consumer prices and a utility function that is separable over time. The investor must therefore maximise his utility by choosing an optimal quantity of asset to buy in the first period. The optimisation programme to be solved is as follows:

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

We denote consumption as c_t in 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":

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

with

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

Using the stochastic discount factor involves weighting income on the asset differently depending on the relative marginal utility of consumption over the two periods. If consumption in $t+1$ is high compared to that in t, given that marginal utility diminishes, the discount factor is small. This means that the income arising from the asset in this case is weighted less. Conversely, if consumption is low, income from the asset is high for the consumer, who gives it greater weighting.

To express the risk premia, it is necessary to derive the gross return on the asset. To do so, we divide income x_{t+1} by the price p_t ((i.e. $R_{t+1} = x_{t+1}/p_t$). We obtain:

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

Risk-free asset

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:

$$1 = E(m_{t+1} R^f_{t+1}) = E(m_{t+1}) R^f_{t+1}$$

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

Risk premium

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

Considering equations (5) [20] and (6), we have:

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

The risk premium therefore equals minus the covariance of the return on the risky asset with the stochastic discount factor multiplied by the risk-free rate.

Price and quantity of risk

The risk premium can be decomposed as follows:

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

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

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

which can be written in the form:

$$E(R^i_{t+1}) = R^f_{t+1} + \beta_{i,m}\,\lambda_m \tag{10}$$

with :

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

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

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 article. However, to avoid any confusion, it needs to be distinguished from the parameter of risk aversion in the consumer's utility function.

Distinction between the risk aversion parameter in the utility function and the price of risk

We use 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 stochastic discount factor is then written:

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

20 *Which can be developed using the definition of covariance*, $cov(m_{t+1}, R_{t+1}) = E(m_{t+1}, R_{t+1}) - E(m_{t+1})\,E(R_{t+1})$.

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

$$E(R^i_{t+1}) = R^f_{t+1} + \beta_{i,\Delta c}\,\lambda_{\Delta c} \qquad (14)$$
$$\lambda_{\Delta c} = \gamma var\,(\Delta c)$$

The price of risk $\lambda_{\Delta c}$ is determined by the risk aversion parameter γ and by the volatility of consumption. Expected returns increase linearly with their betas and the volatility of consumption.

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 (1965) may be considered a particular case of the CCAPM. We therefore express the stochastic discount factor depending on the return, denoted R^w_{t+1}, on the "wealth portfolio" held by the consumer. This return R^w thus serves to approximate the marginal utility of consumption:

$$m_{t+1} = a - bR^w_{t+1} \qquad (15)$$

a and b are parameters > 0

It is then possible to approximate R^w by the return on a broad portfolio of stocks regarded as the market portfolio. This can be a large stock index such as the EuroStoxx 50 or the S&P 500. 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 stochastic discount factor will then be:

$$m_{t+1} = a - bR^m_{t+1} \qquad (16)$$

This formulation is consistent with the previous model of consumption in which the market return plays a similar role to that of changes in consumption in the previous model.

Link with a factor model

The stochastic discount rate is expressed as a function of a number of factors f, which may be different from consumption or market returns.

$$m_{t+1} = f_{t+1}{}'\,b \qquad (17)$$

If we consider that factors f are not directly observable, a factor analysis method is needed to estimate them (see Cochrane, 2001, p.175).

APPENDIX 2

The GRAI: risk aversion represented by the correlation between volatility and price changes

The framework is given by a CAPM model of the type:

$$E(R^i_{t+1}) - R^f_{t+1} = \rho \, cov\,(R^i_{t+1}, R^m_{t+1}) \tag{1}$$

with ρ representing risk aversion and R^m being the return on the market portfolio, equal to the return on all of the assets in this portfolio weighted according to their importance in the portfolio index α_i, so that:

$$R^m_{t+1} = \sum_i \alpha_i R^i_{t+1} \tag{2}$$

If we add an assumption of independent returns on different markets, the risk premia on each security no longer depend on the covariance with other premia, but only on the security's variance (denoted σ^2_i).

$$E(R^i_{t+1}) - R^f_{t+1} = \rho \, cov\,(R^i_{t+1}, \alpha_i R^i_{t+1}) = \rho \alpha_i \sigma^2_i \tag{3}$$

By deriving formula [3] in relation to ρ, we obtain the change in the expected risk premium when risk aversion increases:

$$\frac{\partial\,[E(R^i_{t+1}) - R^f_{t+1}]}{\partial \rho} = \alpha_i \, \sigma^2_i \tag{4}$$

Thus, an increase in risk aversion results in an increase in the expected risk premium that is proportional to the volatility of the asset's return, according to equation (4).

By deriving formula (3) in relation to σ^2_i, we obtain the change in the risk premium when the asset's volatility, i.e. the risk associated with it, increases:

$$\frac{\partial\,[E(R^i_{t+1}) - R^f_{t+1}]}{\partial \sigma^2_i} = \rho \, \alpha_i \tag{5}$$

Equation (5) shows that an increase in an asset's volatility brings about an increase in the risk premium on this asset that is proportional to the risk aversion, but does not depend on the initial volatility.

To calculate GRAI indicators, variations in prices rather than expected excess returns are used, which explains the change in sign in the correlation.

The expected return equals the anticipated change in price:

$$E(R^i_{t+1}) = E(P^i_{t+1}) - P_t \tag{6}$$

By assuming that $E(P^i_{t+1})$ is constant and using (6) and (3), we obtain:

$$\frac{\partial\,[P_t]}{\partial \rho} = -\,\alpha_i \sigma^2_i \tag{7}$$

The GRAI indicator is therefore a correlation with a negative sign between price changes of the different assets and their volatility.

APPENDIX 3

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.

• Four OAS corporate bond spreads for the euro area and the United States:[21] for each area, one spread for investment grade and another for speculative grade. These spreads are calculated by Merrill Lynch.

• Two spreads for emerging markets: first, the EMBI Global,[22] representing the risk premium on their dollar-denominated external sovereign debt, calculated since mid-1998 by JP 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.

• Two swap spreads, one for the euro area and one for the United States.

Crisis indicators

Currency crises

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.

21 *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).*
22 *The Emerging markets bond index Global (EMBI Global) is an index that represents the average price of bonds in emerging market countries.*

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 11.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 crises

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.