How does investor sentiment affect stock market crises? Evidence from panel data

Mohamed ZOUAOUI
University of Franche-Comté LEG (FARGO)-UMR 5118

Geneviève NOUYRIGAT
University of Grenoble CERAG-UMR 5820

Francisca BEER
California State University of San Bernardino

FARGO - Centre de recherche en Finance, ARchitecture et Gouvernance des Organisations

Cahier du FARGO n° 1110304
Version 1 – Mars 2011

Résumé : We test the impact of investor sentiment on a panel of international stock markets. Specifically, we examine the influence of investor sentiment on the probability of stock market crises. We find that investor sentiment increases the probability of occurrence of stock market crises within a one-year horizon. The impact of investor sentiment on stock markets is more pronounced in countries that are culturally more prone to herd-like behavior and overreaction or in countries with low institutional involvement.

Mots clés : Investor sentiment, noise trader, stock market crises

JEL Classification : G12, G14, G15

Contact : Mohamed ZOUAOUI; Mohamed.Zouaoui@univ-fcomte.fr, Tel: 0033 381 666 642
Geneviève NOUYRIGAT, Genevieve.nouyrigat@upmf-grenoble.fr, Tel: 0033 475 418 844
Francisca BEER, fbeer@csusb.edu, Tel: 001 909 880 5709

Traditional financial models have difficulty explaining financial crises. The crash of October 1987, for instance, remains enigmatic for researchers. During the crash, stock prices dropped an average of 22.6%, a decrease much larger than what can be explained by changes in economic variables (Black, 1988; Fama, 1989; Siegel, 1992). The view about the market "personality", the market behavioral approach recognizes that investors are not "rational" but "normal" and that systematic biases in their beliefs induce them to trade on non-fundamental information, called "sentiment". Baker and Wurgler (2007) broadly define “*investor sentiment, as a belief about future cash flows and investment risks that is not justified by the facts at hand*.”

Several theoretical studies offer models establishing the relationship between investors’ sentiment and asset prices (Black, 1986; De Long, Shleifer, Summers and Waldmann, 1990). Two categories of investors characterize these models: informed traders, who rationally anticipate asset value, and uninformed noise traders, who experience waves of irrational sentiment. Rational traders, who are sentiment free, correctly evaluate assets. Uninformed noise traders’ overly optimistic or pessimistic expectations provoke strong and persistent mispricing. In these models, informed traders and noise traders compete. Informed traders, the unemotional investors, who force capital market prices to equal the rational present value of expected future cash flows, face non-trivial transactions and implementation costs as well as the stochastic noise traders’ sentiment. These elements prevent them from taking fully offsetting positions to correct mispricing induced by noise traders. Hence, to the extent that sentiment influences valuation, taking a position opposite to prevailing market sentiment can be both expensive and risky. Mispricing arises out of the combination of two factors: a change in sentiment on the part of the noise traders and a limit to arbitrage.

Several empirical studies attempt to measure investor sentiment (Lee, Shleifer and Thaler, 1991; Brown and Cliff, 2004). These studies identify direct and indirect sentiment measures.

Direct sentiment measures are derived from surveys, while indirect measures rely on objective variables that correlate with investor sentiment. Numerous significant publications focus on the impact of sentiment on future stock returns (Fisher and Statman, 2000; Brown and Cliff, 2005). Findings show that individual investors are easily swayed by sentiment. Sentiment indicators increase the traditional model’s explanatory power for stocks that are traditionally more difficult to arbitrage and to value, e.g. small stocks, value stocks, stocks with low prices and stocks with low institutional ownerships.

Despite the number of published works on the issue of investor sentiment, several avenues of research remain unexplored. In particular, the empirical question of a relationship between sentiment and stock market crises remains under-researched and unresolved. Fluctuations in investors’ sentiment are often mentioned as a factor that could explain the financial crises but rarely are analysed (De Long and Shleifer, 1991; Shiller, 2000). Few studies attempt to directly link sentiment indicators to market crises. Only two studies are identified and those are limited to the U.S. stock market crash of 1987 (Siegel 1992; Baur, Quintero and Stevens, 1996).

Our goal, therefore, is to study the ability of sentiment indicators to predict the occurrence of international stock market crises. Our study focuses on stock market crises, rather than events of abnormal price run-ups. Shefrin and Statman (1985) and Daniel, Hirshleifer and Subrahmanyam (1998) show that negative news and positive news produce different sentiment driven biases. To achieve our objective, we build a "leading indicator" of crises using data from 16 countries. By means of a logit model, we relate our qualitative crises indicator to a set of quantitative macro-economic variables and the indicator of sentiment. Specifically, we test whether consumer confidence - as a proxy for individual investor sentiment- influences the probability of stock market crises in 16 countries. Results confirm the significant impact of investors’ sentiment on financial crises. The impact of sentiment is more pronounced for countries that are culturally more prone to herd-like behavior and overreaction and countries with low institutional development.

Our study diverges from previous research in several ways. First, we add a proxy for investors' sentiment to serve as an indicator of financial crises. A better grasp of stock market crises should deepen our understanding of the dynamic process of stock price adjustments to intrinsic value. Second, our sample of different countries allows comparisons with U.S. data. Pooling data is also known to increase the power of statistical tests providing better estimates (Ang and Bekaert, 2007)[1]. Third, taking an international perspective allows us to analyse the cross-country variations in the sentiment-return relationship. A cross-country study can provide evidence on how cultural differences as well as institutional differences affect the sentiment-return relation.

The remainder of this article is organized as follows. The second section is devoted to a summary of the literature. The third section presents the methodology and variables used to explain the probability of a stock market crisis. The fourth section analyzes the empirical results obtained. The fifth section investigates cross-country results. The sixth section concludes the study.

2. Literature Review

The relationship between the variables sentiment and stock returns is at odds with classic finance theory, which states that stock prices mirror the discounted value of expected cash-flows and that the impact on asset prices of market participants' irrational behavior are removed by arbitrageurs. Behavioral finance, on the other hand, suggests that optimistic and/or pessimistic investors' expectations affect asset prices. Baker and Wurgler (2006) point out that sentiment-based mispricing is based on an uninformed demand of some investors, the noise traders, and a limit to arbitrage.

---

[1] Notice however that due to the cross-correlations between countries, we probably have fewer than 16 independent observations.

The process by which security prices adjust to the release of new information has also been studied extensively. Results of these studies show that stock prices reflect more than fundamental variables. Niederhoffer (1971) highlights the weak stock market reaction to events considered important (election, war, change of foreign leadership…, etc,) while very strong asset price variations remain difficult to explain. Cutler, Poterba and Summers (1991) establish that macro-economic variables explain approximately a third of the variance in stock returns.

The stock market crises have led several well renowned financial economists to distance themselves from the traditional finance theory. Shiller (1987) surveys both individual and institutional investors inquiring about their behavior during the 1987 crash. The survey reveals that most investors interpret the crash as the outcome of other investors' psychology rather than fundamental financial variables such as earnings or interest rates. Siegel (1992) confirms that changes in corporate profits and interest rates are unable to explain the rise and subsequent collapse of stock prices in 1987. He suggests that a shift in investor sentiment is a factor in the stock market's deep decline[2].

The link between asset valuation and investor sentiment is the subject of considerable deliberation among financial economists. A vast number of empirical investigations with different measures of investor sentiment have been undertaken. Brown and Cliff (2004) scrutinize various direct and indirect sentiment indicators. They report that direct (surveys) and indirect measures of sentiment are correlated. Although indicators of sentiment strongly correlate with contemporaneous market returns, they show that sentiment has little predictive power for near-term future stock returns. Qiu and Welch (2006) show that although indirect measures circumvent the lack of sample size and statistical representativeness of the direct

[2] On the other hand, Baur, Quintero and Stevens (1996) report that during the periods that surrounded the crash, only changes in fundamentals have a statistically significant impact on the movement of stock prices. Other studies show that traditional models are sufficient to explain the variations of stock market when volatility factors are added (Goyal and Santa-Clara, 2003).

measurements, the theoretical link to investor sentiment is weaker than with the direct indicators.

Contrary to previous findings, using survey data, Brown and Cliff (2005) show that excessive optimism leads to periods of market overvaluation and high current sentiment is followed by low cumulative long-run returns. Baker and Wurgler (2006) construct an index of investor sentiment as the first principal component of six indirect investor measures suggested in the literature. They find that the sentiment effects are stronger among stocks whose valuations are highly subjective and difficult to arbitrage.

Previous studies provide evidence related to US markets. Very recently, studies focus on international data. Schmeling (2009) examines whether investor sentiment, as measured by a consumer confidence index, influences expected stock returns in 18 industrialized countries. In line with recent evidence for the U.S, he finds that, on average, sentiment negatively forecasts aggregate stock market returns across countries. This relationship also holds for returns of value stocks, growth stocks, small stocks, and for different forecasting horizons. Similarly, Baker, Wurgler and Yuan (2009) put together indices of investor sentiment for six major stock markets and decomposed them into one global and six local indices. They determine that sentiment, both global and local, is a statistically and economically significant contrarian predictor of market returns, particularly for stocks whose valuation are highly subjective and difficult to arbitrage.

The prior literature review highlights the lack of consensus about the best measure of sentiment or on whether sentiment affects stock prices. Our paper is most closely related to Schmeling (2009) and Baker, Wurgler and Yuan (2009) who use international data. The present study differs from theirs in that it is the first research to directly link sentiment indicators to international stock market crises. We propose to test the impact of investor sentiment on international capital markets by studying its ability to predict the occurrence of stock market crises. A priori, stock market crises should be preceded by periods of rising investor euphoria. Therefore, we expect that periods characterized by excessive investors' optimism are followed by stock market crises.

3. The stock market crises and the role of investor sentiment

Our study includes 15 European countries and the United States. Data includes monthly observations for the period between April 1995 and June 2009. Economic data availability dictates the beginning time period for most countries. As discussed below, our study includes financial and macro-economic variables and survey results. The list of the countries and the data sources are presented in table 1.

[INSERT TABLE 1]

3.1. Identification of stock market crises

The first step of our study consists of identifying the financial crises that have occurred during the period considered in the regions studied. To achieve this goal, we use the methodology proposed by Patel and Sarkar (1998) which is, according to these authors, widely used by practitioners.

In their study, Patel and Sarkar (1998) designed a crises indicator called CMAX. The CMAX compares the current value of an index with its maximum value over the previous T periods, usually 1 to 2 years. The CMAX ratio is calculated by dividing the current price by the maximum price over the previous two-year period[3].

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

Where P_{it} is the stock market index at time t for country i. The rolling maximum in the denominator is defined over a relatively short period (24 months) to avoid losing too many data points.

[3] Similar to Mishkin and White (2002), we define a stock market crash as a 20 percent drop in the market over a window of 12-month, 24-month and 36-month. Findings are similar to those obtained with CMAX.

Boucher (2004) describes the CMAX as an indicator of the decline in volatility. This indicator equals 1 if prices rise over the period considered, indicating a bullish market. The more prices fall, the closer the CMAX gets to 0. A crisis is detected whenever CMAX exceeds a threshold set at the mean of CMAX minus two standard deviations both calculated on the whole sample. To avoid counting the same crisis more than once, a crisis is automatically eliminated if detected twice over a twelve-month period.

The stock market crises indicator for country i at time t, $C_{i,t}$, is defined as follows:

$$C_{i,t} = 1 \text{ if } \mathrm{CMAX}_{\mathrm{i,t}} < \overline{CMAX}_i - 2\,\sigma_i$$
$$C_{i,t} = 0, \text{ otherwise}$$

Given the indicator structure, share price decreases are already well in progress when a crisis is identified, i.e. $C_{i,t}$ uncovers abnormal drops in prices rather than the market turning points. This indicator only identifies as crises those events that eliminate the previous two years of gains.

Similar to Patel and Sarkar (1998), we define the following concepts : (i) the beginning of the crisis is the month when the index reaches its historical maximum over the 2-year window prior to the month when the crash is triggered; (ii) the beginning of the crash corresponds to the month when the CMAX intersects with a threshold; (iii) the date of the trough is the month when the price index reaches its minimum; (iv) the date of recovery is the first month after the crash when the index reaches the pre-crash maximum; (v) the magnitude of the crisis is the difference between the value of the index at its maximum and at its minimum; (vi) the length of the trough is the number of months between the date of the beginning of the crisis and the date of the trough; and (vii) the length of the recovery period is the number of months for the index to return to the maximum.

Figure 1 illustrates these concepts by using the US stock market. As shown, three crises[4] are identified during the period 1995-2009. The first crash occurs in July 2001 and reaches a trough eleven months later in June 2002. It is characterized by a decrease of 40% in the S&P500. The crisis ended 81 months later, in April 2007. The second crash takes place in August 2002. It took 52 months for the market to regain the 43% loss during the crisis. The third crash is identified in June 2008 and the magnitude of this crisis is 52.55 %.

Table 2 presents the characteristics of the crises identified in our sample. During the period analyzed, we detect 44 crises, i.e. an average of 2.75 per country. Most of these crises correspond to well known historical events, such as the internet bubble of the 2000's and the recent subprime crisis. Consistent with Roll (1988) who indicates substantial price increases in many international stock markets in the nine months prior to the October 1987 stock crash, the average returns before the crises are high. The three-year pre-crises annual median return is equal to 86.38% and the one year pre-crises annual median return is 31.6%.

[INSERT TABLE 2]

3.2. The methodology used to link investor sentiment to stock market crises

The seventies saw the emergence of the first models for forecasting crises including banking crises and currency crises (Early Warning Models or Early Warning Signals). Most of these models use discriminant analysis and logit/probit models. Logit/probit models help to isolate "leading indicators" of financial crises[5]. The idea underlying these models is to identify economic variables having a specific behavior before the onset of the crises and to estimate the probability of occurrence of these crises during a specific period (usually one or two years), taking into account the information these variables included (Frankel and Rose,

[4] Further, to avoid counting as distinct crises, episodes that are so close together that they could represent parts of the same crisis, we also eliminate a crisis if detected more than once over a period of 24-months or 48-months. As findings for a 12-month, the 24-month and the 48-month periods are identical, we rely on a 12-month window to take advantage of as many observations as possible. Also note that as far as the US is concerned a window of 20-months identifies only two crises, 2001 and 2008.

[5] Discriminant analysis is not designed to determine the causes of crises, but rather to separate groups.

1996; Bussiere and Fratzscher, 2006). Our approach, outlined below, is inspired by the logit/probit models.

- **The dependent variable**

The logit model of the occurrence of a crisis with lagged values of early warning indicators as explanatory variables requires the construction of a crisis dummy variable that serves as the endogenous variable in the regression. To construct our dependent variable, we closely follow the methodology of Brussiere and Fratzcher (2006). Using the crises identified above, we define a dummy variable $I_{i,t}$. $I_{i,t}$ equals 1 during the crises and the twelve months preceding the crises and 0 during calm time periods. Combining the periods following the crises, with the quiet periods might distort the estimations of the logit model. To avoid such biases, the 11-month periods following the crises are left out of the estimations.

$$
\begin{aligned}
&I_{i,t} = 1 \text{ if } \exists\, \mathrm{k} \in \{1,...,12\} \text{ such as } \mathrm{C}_{\mathrm{i,t}+k} = 1 \\
&\mathrm{I}_{\mathrm{i,t}} = n.a \ \text{ si } \exists\, \mathrm{k} \in \{1,...,11\} \text{ such as } \mathrm{C}_{\mathrm{i,t-k}} = 1 \\
&\mathrm{I}_{\mathrm{i,t}} = 0, \ \text{otherwise}
\end{aligned}
$$

Bussiere and Fratzscher (2006) also argue that incorporating the period immediately following the crisis by using multinomial logit estimation can improve the model's forecasting accuracy. Incorporating post-crisis periods could also show what happens to investor sentiment in the months following the crisis. Thus, we construct a second dependent variable, $J_{i,t}$, with three outcomes. It equals 0 during calm time periods, 1 during the crises and the twelve months preceding the crises and 2 during the eleven months following the crises.

$$
\begin{aligned}
&J_{i,t} = 2 \text{ if } \exists\, \mathrm{k} \in \{1,...,11\} \text{ such as } \mathrm{C}_{\mathrm{i,t}-k} = 1 \\
&\mathrm{J}_{\mathrm{i,t}} = \mathrm{I}_{\mathrm{i,t}}, \ \text{otherwise}
\end{aligned}
$$

- **The independent variables**

The following sub-sections present the variables proposed to explain the crises detected in the sample. The first sub-section introduces "traditional" variables. The second sub-section focuses on the variable sentiment.

- **The traditional variables**

Contrary to banking and currencies crises where studies are abundant, very few studies have been published about the variables explaining stock market crises. These variables, mostly identified by Boucher (2004) and Coudret and Gex (2008) are the volatility index (VIX), the year-on-year change in stock prices (RET), the price earnings ratios (PER), the inflation rate (INF), the real interest rate (INT) and the ratio domestic credit/GDP (CREDIT).

VIX, the implied volatility of options, is a measure of how much investors are willing to pay as a safeguard against the risk of price fluctuations. The VIX is a measure regarded by many market analysts as a direct gauge of fear (CBOE, 2004). Coudert and Gex (2008) find that the risk aversion indicators such as VIX are leading indicators of stock market crises. RET is a good substitute for price acceleration and decline. Indeed, the stock market returns tend to decline gradually before the onset of the crisis. The variable PER is widely used as predictor of stock returns downturns. Campbell and Shiller (2001) show that when stock market valuation ratios are at extreme levels by historical standards, some weight should be given to the mean-reversion theory that prices will fall in the future to bring the ratios back to more normal historical levels.

Stock prices are negatively correlated to inflation and financial crises are characterized by high volatility of inflation. For example, Fama and Schwert (1977) establish that most stock markets have the tendency to perform poorly when inflation is high. Using US data since 1789, Bordo and Wheelock (1998) show that most financial crises occurred during periods with high variation in inflation. The interest rates are also often cited as a good indicator of financial crises. Interest rates tend to decline significantly before the collapse of stock markets.

Finally, the variable CREDIT is used to capture financial instability often visible before financial crises. As documented in Goldstein (1998) and Kamin (1999), when domestic credit grows at a faster rate than GDP, this can lead to excessive risk-taking from investors with large losses on loans in the future. With the rapid growth of lending, banking institutions might not be able to add the necessary managerial capital (well-trained loan officers, risk-assessment systems, etc.) fast enough to enable their institutions to screen and monitor these new loans appropriately. The outcome of the lending boom leads to the deterioration in bank balance sheets, leading economies into financial crises.

- **The behavioral variable**

A universally accepted measure of investor sentiment has not yet been identified. For this study, we favor the consumer confidence index. The use of the consumer confidence index appears logical. First, our selection is the result of the established relationship between the consumer confidence index and equity market. Recent studies show that the consumer confidence index seizes some of the stock market aspects not already contained in traditional macro-economic indicators[6]. Second, the data on the consumer confidence index has been available for the majority of developed countries since the mid-80s. Third, as most countries use similar surveys to gather data, comparisons across countries are possible. The European surveys include questions about respondents' views of the economic situation, their financial situation and their purchase of durable goods. These surveys are harmonized since the mid-80s and the questions are similar to those asked by the Survey of the University of Michigan[7].

The consumer confidence index seems to be the preferred sentiment indicator of numerous researchers. Qiu and Welch (2006) and Lemmon and Portniaguina (2006) and Ho and Hung (2009) present several additional arguments in support of this variable:

- Although consumers polled for the consumer confidence index are not asked directly for their views on security prices, changes in the consumer confidence index correlate

[6] See Charoenrook (2006), Qiu and Welch (2006) and Lemmon and Portniaguina (2006).
[7] Notice, however, that the European surveys ask respondents to focus on a one-year horizon while the Michigan survey asks for one-year horizon when a household's financial situation is concerned but for 5-year horizons for economic developments. The survey size also varies per country. Generally, the European surveys' sample sizes are larger than those of University of Michigan surveys.

very highly with changes in stock prices. More importantly, Figure 1 shows that the US consumer confidence index roughly lines up with anecdotal evidence of fluctuations in sentiment. The consumer confidence index significatively decreases in 2000 and 2008.

- Participation of individual households in financial markets has increased substantially over recent years, suggesting that measures of consumer confidence may be a useful barometer for how individual investors feel about the economy and the financial markets.
- Researchers utilize longitudinal data, which allows for more robust and significant studies. Measures of sentiment derived from surveys circumvent some of the drawbacks of indirect measures[8].
- Because the consumer confidence index captures individual beliefs, it reflects the philosophy of behavioral finance by including the opinions of imperfect people who have social, cognitive, and emotional biases (Shleifer, 2000).

Finally, as many researchers[9] emphasize that sentiment indicator reflects an economic component and a psychological aspect, we decompose the consumer confidence index into a component related to the business cycle, i.e. macroeconomic "fundamentals" and a residual component that we interpret as a purer measure of "sentiment" ($SENT^{\perp}$). Specifically, we treat the residuals from the following regression as our measure of sentiment unwarranted by fundamentals:

$$SENT_{i,t} = \alpha + \beta_j \sum_{j=1}^{J} FUND_{i,t}^{j} + \varepsilon_{i,t}$$

The variables that capture the component related to the business cycle, i.e. macroeconomic "fundamentals" (*FUND*) are: (i) the changes of the industrial production (IP);

[8] Because indirect measures are made up of time series of macro-economic and financial variables, they may not exclusively represent investors' sentiment.

[9] See Brown and Cliff (2005), Kumar and Lee (2006) and Baker and Wurgler (2006).

(ii) the growth in consumption of durables (CD); non-durables (CND) and services (CS); (iii) the term spread defined as the difference in yield between the 10-year and 3-month government bonds (ST); and (iv) the dividend yield measured as the dividend divided by the market capitalization (DY). We believe that these variables are as comprehensive as those commonly used in the literature. This procedure reduces the likelihood that variation in sentiment is related to systematic macroeconomic risks. The sentiment measure is orthogonalized with respect to several contemporaneous variables.

- **The model used**

The dependent variable $I_{i,t}$ or $J_{i,t}$ are explained by the macro-economic indicators and the variable sentiment via a logit model. In seeking to estimate the probability that the variable $I_{i,t}$ or $J_{i,t}$ is equal to 1, we estimate the probability of a crisis within a 1-year window. In other terms, the model attempts to predict whether a crisis will occur during the coming 12 months rather than the exact timing of a crisis. Bussiere and Fratzscher (2006) highlight that as it is already challenging to predict whether or not a crisis will happen, it is difficult to determine its precise timing.

Specially, we successively estimate three different logit models per dependent variable. Model 1 includes only macro-economic variables. Model 2 focuses on sentiment variable. Model 3 combines macro- economic and sentiment variables[10].

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

$$\Pr(I_{i,t} = 1) = f(\alpha_0 + \alpha_{n+1} SENT_{i,t}^{\perp}) \tag{2}$$

$$\Pr(I_{i,t} = 1) = f(\alpha' + \sum_{k=1}^{n} \alpha_k \; X_{i,t}^{k} + \alpha_{n+1} SENT_{i,t}^{\perp}) \tag{3}$$

In the equations above, $I_{i,t}$ is the crisis indicator variable defined above, X^k the matrix of explanatory variables, α_k the vector of coefficient estimates and “f” a logistic function of the type : $f(z) = \dfrac{e^z}{1+e^z}$.

[10] The explanatory variables have been standardized to insure comparability for all countries.

For multinomial models, we estimate the same equations using J instead of I. Due to lack of space, we present completed results for $I_{i,t}$ and limited ones for $J_{i,t}$.

3.3. The model forecasting ability

To evaluate the performance of the model, we use the signals approach (Kaminsky, Lizondo and Reinhart, 1998; Bussiere and Fratzscher, 2006). The method compares the probability of a crisis generated by the model, the models predicted probability, with the actual occurrence of a crisis. As the predicted probability is a continuous variable, we must decide on a cut-off or threshold probability above which the predicted probability can be interpreted as sending a signal of a pending crisis. The model performs well if the predicted probability corresponds to a crisis as identified in our sample. As shown in table 3[11], four situations are possible:

[INSERT TABLE 3]

Table 3 shows two kinds of errors. In the case of type A errors, the model does not detect actual crises while the type B errors incorrectly identify crises that do not occur. A perfect indicator would only produce observations that belong to the north-west and south-east cells of this matrix, minimizing the type A and type B errors.

The performance of logit model depends largely on these two types of errors. The main question is the optimal threshold level. The lower the threshold, the more signals the model will send with the drawback of having numerous false signals. By contrast, raising the threshold will reduce the number of false signals at the expense of an increase in the number of missed signals. Notice, however that the costs associated with the two types of errors are not the same. Type A errors, missing a crisis that ended up materializing, are larger than type B errors, consisting of incorrectly anticipating a crisis that will not occur. As suggested by

[11] The table is identical when $J_{i,t}$ is used as a dependent variable.

Berg and Patillo (1999) and Coudert and Gex (2008), we decided to present the results for alert thresholds set at 25% and 50%[12].

4. Regression results

Our goal is to estimate the incremental predictive power of the sentiment variable compared to other variables habitually used in the literature. The findings are presented in three parts. Part 1 shows the results of a model including the fundamental economic and financial variables. Part 2 focuses on the sentiment variable. Part 3 combines economic, financial and sentiment indicators. Table 4 presents the results.

[INSERT TABLE 4]

4.1. The predictive power of the traditional variables

With the exception of the variables VIX and INF, all macro-economic variables included in Model 1 are significant and display the expected sign. The model is performing well, the maximum likelihood confirms the quality of the overall fit of the model and the hypothesis of joint nullity of all the regression coefficients except the constant can be rejected.

These findings add credibility to PER, RET, INT and CREDIT as predictors of financial crises. Our study shows that an increase in the PER is positively correlated with the probability of a financial crisis. This result supports the mean-reversion theory that when prices are high they will fall, bringing the PER back to normal historical levels.

The variable INT exhibits a negative and significant coefficient. This result explains why monetary authorities cut rates to stabilize the economy and limit the adverse consequences of bursting bubbles. The sign is also negative for the variable RET, which already tends to decline at the onset of the crisis. As far as the variable CREDIT is concerned, a positive and significant coefficient supports previously reported studies that financial aggregates, such as domestic credit, are early indicators of financial crises. Rapid credit growth has been

[12] Notice that robustness check using different alert thresholds do not change the performance of the models.

associated with macroeconomic and financial crises, originating from macroeconomic imbalances and banking sector distress. This is why policymakers face the dilemma of how to minimize the risks of financial crises while still allowing bank lending to contribute to higher growth and efficiency.

The variable VIX displays the expected sign but is not statistically significant[13]. This result is different from that presented by Coudert and Gex (2008) who report that risk aversion indicators significantly increase before financial market crises. Our different result might be explained by the different samples of countries and by the different time periods characterizing the two studies. More importantly, different results may be due to the different set of macro-economic variables used in the studies.

Contrary to our expectations, the variable INF is negatively correlated to the probability of a financial crisis. A significant negative coefficient is intuitively difficult to comprehend as it implies that policymakers' commitment to price stability increases the probability of a crisis. A negative correlation, can however, be explained by the “paradox of credibility”. Goodfriend (2001) and Borio and Lowe (2002) show that when inflation is under control, tensions of productivity cannot be detected by inflation numbers but rather by instability in the financial sector[14]. The idea has been shared by the BIS economists, who have been arguing along these lines for years, finding more sympathetic ears among central bankers than among academics.

McFadden R^2 statistic is 40.8%, showing the quality of the regression. The results also show that the percentage of crises correctly predicted is high. Type A errors are low showing that the model predicts correctly 65% (threshold 50%) and 72% (threshold 25%) of the crises.

[13] Results for the risk indicators GRAI and RAI are identical to those presented for the variable VIX. The results are not reported due to space limitation.

[14] The bursting of the technology bubble in the beginning of the year 2000 and the recent subprime crises took place at the bottom of a relatively stable period.

Note also that Types B errors (false alarms) are relatively low for the two thresholds (13.62% when the threshold is 50% and 20.24% when the threshold is 25%).

4.2. The predictive power of the variable sentiment

Results from the second model tend to confirm our hypothesis about the variable $SENT^{\perp}$. The variable is statistically significant and it shows the expected positive sign. The model predicts correctly 47% and 68% of the crises at thresholds of 50% and 25% and the percentages of Type B errors are low (13.27% when the threshold is 50% and 16.21% when the threshold is 25%).

Our result corroborates one of the fundamental hypotheses of behavioral finance, that there is a negative relationship between investors' sentiment and the future performance of stocks (Lee, Shleifer et Thaler, 1991; Schmeling, 2009). When investor sentiment is low, subsequent returns are relatively high. On the other hand, when sentiment is high, the pattern is reversed; stocks are overpriced and will experience a decline in value. Stocks market bubbles coincide with periods of overly optimistic investors. However, every mispricing must eventually be corrected so excessive optimism (overvaluation of the market) will inevitably be followed by sharp drops in stock prices (stock market crises).

4.3. The incremental predictive power of the variable sentiment

Results of the third model show that the variable $SENT^{\perp}$ remains significant even after controlling for the financial and economic variables. Results also indicate that with the exception of VIX and PER, all fundamental variables remain significant and keep their expected signs.

These findings suggest that the use of variable sentiment, rather than the traditional PER, improves our ability to predict stock market crises. Indeed, when the sentiment indicator is introduced in the model, the price-earnings ratio loses its explanatory power. This result is similar to that reported by Fisher and Statman (2006) who find that the direct investor sentiment (Investor Intelligence) measure provides better guidance for market timers than do the PER ratio or dividend yields. This result is consistent with the notion that the consumer confidence index is a better proxy of sentiment that the PER[15].

This is a significant result, as the price-earnings ratio is always the focus of management. This result should be pleasing to financial analysts who often complain that the PER multiples are unsophisticated discount factors, failing to account for, among many factors, interest rates and/or inflation rates over the forecast periods.

The model displays good results. The introduction of variable $SENT^{\perp}$ improves the statistical quality of the model; the McFadden R^2 gains about 6% when compared to the first model. The model also predicts correctly 75% and 84% of the crises at thresholds of 50% and 25%. Adding a sentiment indicator, in addition to macroeconomic variables, improves the model prediction of the stock market crises[16].

Findings using the multinominal logit estimations are very similar. We find that the multinominal models do not significantly improve the predictive power of the model, both in terms of quality of regressions and quality of forecasts[17]. However, we find that the post-crisis periods are characterized by negative and significant coefficients for the proxy sentiment. This result is interpreted as an indicator that investor optimism decreases just after the crises, returning to more reasonable levels.

4.4. Out-of-sample performance of logit model

[15] In the same way as Fisher and Statman (2006), we divide the PER into a component related to the fundamental value and a measure of sentiment calculated as the level PER minus the median PER as a proxy for the fundamental value. Results indicate the consumer confidence index is a better proxy for sentiment than the PER. These results are also supported by Qui and Welch (2006) who compared the consumer confidence index with the closed-end found discount.

[16] One potential drawback of the logit model with pooled data is that it ignores the cross-section and time series dimensions of the data. For example, the legal system or the political situation of a country could be such that we permanently understate the probability of a stock market crisis (see Brussiere and Fratzcher, 2006, p.960). To check the robustness of our results, we also estimate panel logit model with fixed and random effects. The results obtained are virtually the same. This suggests that ignoring country-specific information does not constitute a bias in our estimation. Results are available upon request.

[17] Results are available upon request.

If relatively low percentages of errors are necessary to establish the quality of the model, it is not sufficient to conclude that the model is efficient (Berg and Pattillo, 1999). The logit model should be estimated over a given period, then simulated out-of-sample. To test whether our model is able to predict crises out-of-sample, we estimate the model between April 1995 and December 2007 and compute the probability of a crisis in the following 12 months. The goal is to test the accuracy of predictions on out-of-sample data, i.e., the crisis at the end of our sample (the subprime crisis in 2008).

We find that the model is performing well, even out-of-sample, predicting most of the subprime crises occurring during the year 2008. The model failed to predict only the crisis of Denmark in September 2008; the predicted probability of a stock market crisis in Denmark is equal to 0.191[18]. Overall, the out-of-sample performance of our model is robust and would have allowed the correct anticipation of the most recent subprime crisis.

5. Cross-country analyses

We examine whether our results are sensitive to the countries that have been divided into two groups depending on some determinants of market integrity and herd-like overreaction. Specifically, we use our cross-section of countries to determine if there is evidence that the impact of sentiment on stock market crises is higher for countries with less market integrity and for countries culturally prone to overreaction-like behavior and herd behavior.

Market integrity means that financial markets with higher level of institutional sophistication are characterized by a better flow of information and are consequently more efficient. The market integrity variables selected in our study can also be found in La Porta, Lopez-de-Silanes, Shleifer and Vishny (1998), Schmeling (2009) and Chui, Titman and Wei

[18] For Denemark, the out-of-sample predicted probability of a crisis in the following 12 months is below the 25% threshold. Detailed results are available upon request.

(2010). These variables include (i) the index of anti-director rights; (ii) the corruption perception index; and (iii) the accounting standards index[19].

The variables used to assess herd-like overreaction are rooted in an article by Hofstede (2001). The first index measures the level of individualism of a country and the second one, the so-called uncertainty avoidance index measures an individual's attitude toward new and unexpected occurrences. According to Hofstede (2001), individualism affects the degree to which people display an independent behavior rather than a dependent behavior. The author argues that children in collectivistic cultures build their identity from their social system. He shows that higher levels of collectivism indicate a tendency towards herd-like behavior. The uncertainty avoidance index measures the degree to which a culture programs its members to react to new and unusual situations. Hofstede (2001) documents that people in countries with high uncertainty avoiding levels react in a more emotional way compared to countries with low levels of uncertainty avoidance. Therefore we use the uncertainty avoidance as a proxy of the tendency of individuals to overreact. Hofstede (2001) shows that the uncertainty avoidance index is correlated with the collectivism index since the uncertainty avoidance index captures cross-country differences in the propensity of people to follow the same sets of rules and thus to behave in the same manner. Therefore, higher levels of the uncertainty avoidance behavior should indicate a tendency towards more herd-like behavior. Findings are depicted in Table 5.

[INSERT TABLE 5]

For both groups of countries, the McFadden R^2 is higher when sentiment is added in the model. However, results show that the variable $SENT^{\perp}$ is only significant for the group of countries showing high herd-like behavior and low market integrity. For the other group, $SENT^{\perp}$ is significant when the index uncertainty avoidance is used. Furthermore, the model

---

[19] In order to make results easier to interpret, we have rescaled all market integrity indicators. Higher value indicates higher market integrity.

quality is good. We find that the errors of types A and B are lower for collectivistic countries, countries with high uncertainty avoiding index and countries with low institutional involvement.

We have also run regressions on the full sample of countries and introduced interactive terms between the variables identifying market integrity, herd-like behavior and sentiment. Results show that differences between the groups of countries are significant for both groups of variables. We conclude that the cultural factors and market integrity factors significantly differentiate between high and low sentiment effects.

Findings show that using the variable sentiment improves our ability to predict stock market crises in countries where herd-like behavior and overreaction behavior are strong and where market integrity is low. The evidence in the table indicates that culture has a different effect on stock market crises, a result consistent with the idea that investors in different cultures have different biases.

Conclusion

The general finding of a sentiment-return relation is at odds with standard finance theory which predicts that stock prices reflect the discounted value of expected cash-flows and that the impact of irrational behavior by market participants are eliminated by arbitrageurs. In contrast, the behavioral approach suggests that waves of irrational sentiment, i.e. times of overly optimistic or pessimistic expectations, can persist and affect asset prices for significant periods of time, eventually generating crises. This paper attempts to assess the relationship between investor sentiment and stock market crises.

Specifically, our paper empirically examines the influence of investor sentiment on the probability of occurrence of stock market crises over the period 1995-2009. We use panel data of 15 European countries and the United States to estimate a multivariate logit model. It appears that the sentiment of investors positively influence the probability of the occurrence of stock market crises within a one-year horizon. Furthermore, the investor sentiment provides an incremental predictive power of crises compared to other variables routinely used in the literature. The impact of investor sentiment on stock markets is stronger for countries culturally more prone to herd-like behavior and overreaction and countries with low efficient regularity institutions. These results are important for portfolio managers; investors' sentiment is a good predictor of securities overvaluation. Finally, these are key findings for financial market regulators because investors' sentiment can be useful to anticipate stock market crisis.

References

Ang, Andrew, and Geert Bekaert, 2007, Stock return predictability: is it there?, *Review of Financial Studies* 20, 651-707.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor Sentiment in the Stock Market, *Journal of Economic Perspectives* 21, 129-151.

Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2009, Global, Local, and Contagious Investor Sentiment, *National Bureau of Economic Research (NBER).*

Baur, Michael N, Socorro Quintero, and Eric Stevens, 1998, The 1986-1988 Stock Market: Investor sentiment or fundamentals?, *Managerial and Decision Economics* 17, 319-329.

Berg, Andrew, and Catherine Pattillo, 1999, Are Currency Crises Predictable? A Test, *IMF Staff Papers* 46, 107-138.

Black, Fischer, 1986, Noise, *Journal of Finance* 41, 529-543.

Black, Fischer, 1988, An equilibrium Model of the Crash *NBER Macroeconomics Annual*, 3, 269-275.

Bordo, Michael D., and David C. Wheelock, 1998, Price Stability and Financial Stability: The Historical Record, *Federal Reserve Bank of St.Louis Review* Sep/Oct., 41-62.

Borio, Claudio, and Philip Lowe, 2002, Asset Prices, Financial and Monetary Stability: Exploring the Nexus, *BIS Working Papers* n°114.

Boucher, Christophe, 2004, Identification et comparaison des crises boursières, *Conseil d'Analyse Economique, report*, 50, 375-396.

Brown, Gregory W., and Michael T. Cliff, 2004, Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1-27.

Brown, Gregory W., and Michael T. Cliff, 2005, Investor Sentiment and Asset Valuation, *Journal of Business* 78, 405-440.

Bussiere, Matthieu, and Marcel Fratzscher, 2006, Towards a new early warning system of financial crises, *Journal of International Money & Finance* 25, 953-973.

Campbell, John, and Robert Shiller, J, 2001, Valuation Ratios and the Long-Run Stock Market Outlook: An Update, *National Bureau Of Economics Research* Working Paper 8282.

Charoenrook, Anchada, 2006, Does Sentiment Matter?, *Vanderbilt University*.

Chui, Andy C.W., Sheridan Titman, and K. C. John Wei, 2010, Individualism and Momentum Around the World, *Journal of Finance*, 65, 361-392.

Coudert, Virginie., and Mathieu. Gex. 2008. Does risk aversion drive financial crises? Testing the predictive power of empirical indicators. *Journal of Empirical Finance* 15 (2):167-184.

Cutler, David M., James M. Poterba, and Lawrence H. Summers, 1991, Speculative Dynamics, Review of Economic Studies 58, 529-547.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998. Investor psychology and security market under- and over-reactions, *Journal of Finance* 53, 1839-1885.

De Long, J. B., and A. Shleifer, 1991, The stock market bubble of 1929: Evidence from closed-end mutual funds, *Journal of Economic History* 51, 675-700.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

Fama, Eugene F., 1989, Perspectives on octobre 1989 Or What did we learn from the crash? , *Black Mondy and the Future of Financial Market*, 71-82.

Fama, Eugene, and G.William Schwert, 1977, Asset Returns and Inflation, *Journal of Financial Economics* 5, 115-146.

Fisher, Kenneth L., and Meir Statman, 2000, Investor Sentiment and Stock Returns, *Financial Analysts Journal* 56, 16-23.

Fisher, Kenneth L., and Meir Statman, 2006, Market timing in regressions and reality, *The Journal of Financial Research*, Vol XXIX, N°3, 293-304.

Frankel, Jeffrey A., and Andrew K. Rose, 1996, Currency Crashes in Emerging Markets: An Empirical Treatment, Working Papers, US Federal Reserve Board's International Finance Discussion Papers.

Goldstein, Morris, 1998, The Asian Financial Crisis: Causes, Cures, and Systematic Implications, Institute of International Economics: Washington, DC. 77 pages,

Goodfriend, Marvin 2001, Financial stability, deflation and monetary policy, *Bank of Japan, Special Edition, February*.

Goyal, Amit., and Pedro Santa-Clara, 2003. Idiosyncratic risk matters!, *Journal of Finance* 58, 975-1007.

Ho, Chienwei., and Hung Chi-Hsiou Hung, 2009, Investor sentiment as conditioning information in asset pricing, *Journal of Banking and Finance*, 33, 892-903.

Hofstede, Geert, 2001. Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations across Nations. *Sage Publication, Beverly Hills*.

Kamin, Steven B., 1999, The current international financial crisis: how much is new?, *Federal Reserve System.*

Kaminsky, Graciela, Saul Lizondo, Carmen M. Reinhart, 1998, Leading indicators of currency crises, *IMF Staff Papers* 45, 1-48.

Kumar, Alok, and Charles M. C. Lee, 2006, Retail Investor Sentiment and Return Comovements, *Journal of Finance* 61, 2451-2486.

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny, 1998, Law and finance, *Journal of Political Economy* 106, 1113-155.

Lee, Charles M. C., Andrei Shleifer, and Richard H. Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle, *Journal of Finance* 46, 75-109.

Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer Confidence and Asset Prices: Some Empirical Evidence, *Review of Financial Studies* 19, 1499-1529.

Mishkin, Frederic., White, Eugene, 2002. US stock market crashes and their aftermath: implications for monetary policy. *NBER Working Paper*, vol. 8992.

Niederhoffer, Victor, 1971, The Analysis of World Events and Stock Prices, *Journal of Business* 44, 193-219.

Patel, Sandeep A., and Asani Sarkar, 1998, Crises in Developed and Emerging Stock Markets, *Financial Analysts Journal* 54, 50-61.

Qiu, Lily., and Ivo Welch, 2006, Investor Sentiment Measures, *Brown University and NBER*.

Roll, Richard, 1988, The international Crash of October 1987, *Financial Analysts Journal* 44, 19-35.

Schmeling, Maik, 2009, Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16, 394-408.

Shefrin, Hersh, and Meir Statman, 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of* Finance 40, 777-790.

Shiller, Robert, J, 1987, Investor Behaviour in the October 1987 Stock Market Crash: Survey Evidence, *National Bureau Of Economics Research* Working Paper.

Shiller, Robert J., 2000. *Irrational Exuberance*. *Broadway Book.*

Shleifer, Andrei, 2000, Inefficient Markets: An Introduction to Behavioral Finance in inc. Oxford University Press, ed.: (New York).

Siegel, Jeremy J., 1992, Equity risk premia, corporate profit forecasts, and investor sentiment around the stock crash of October 1987, *Journal of Business* 65, 557-570.

Table 1: Description of variables used in the study

Code	Variables	Measures	Sources
Macroeconomics variables			
INT	Real interest rate	Money market rate[20] using consumer price index	International Financial Statistics
INF	Inflation rate	Change in the natural logarithm of the Consumer Price Index	International Financial Statistics
CREDIT/GDP[21]	Domestic credit	Domestic credit divided by Gross Domestic Product	European central Bank & Federal reserve system
ST	Term spread	Difference between the yields on 10-year government bonds and 3-month Treasury bills	International Financial Statistics
IP	Industrial production	Change in the natural logarithm of industrial production index	International Financial Statistics
CD, CND and CS	Growth of durable goods, non-durables goods and services consumption expenditures	Change in the natural logarithm of durable goods, non-durables and services consumption expenditures	International Financial Statistics
Stock market variables			
P[22]	Stock price index	Stock price index	Datastream
VIX	Volatility Index	Implicit volatility of options prices	Coudert and Gex
PER	Price Earning Ratio	Share price divided by earning per share	Bloomberg
DY	Dividend Yield	Cash dividend of the index divided by the value of the index	Bloomberg
RET	year-one-year change in stock prices	Yearly change in stock prices	Datastream
Investor sentiment indicator			
SENT	Consumer sentiment index	The five questions making up the consumer sentiment index	Economic European Commission & University of Michigan Survey Research Center

[20] Money Market rate is the rate on short term lending between financial institutions. It represents the rate on six-month interbank deposits.
[21] GDP quarterly data have been transformed into monthly data using moving averages. All macroeconomics time series are seasonally adjusted.
[22] The data stock market indices are the following : BEL 20 (Belgium), PRAGUE PX 50 (Czech Republic), OMX Copenhagen (Denmark), DAX 30 (Germany), HE GENERAL IRELAND (Ireland), ATHENS SE GENERAL (Greece), IBEX 35 (Spain) , CAC 40 (France), 30 MILAN COMIT (Italy), ESTONIA TALS INDEX (Estonia), PORTUGAL PSI-20 (Portugal), SLOVENIAN EXCH. STOCK (Slovenia), DJWI FINLAND (Finland), SWEDEN OMX (Sweden), FTSE 100 (U.K) and the S&P 500 Composite (U.S.).

Table 2: Characteristics of individual market crises

This table presents the characteristics of the stock market crises. The beginning of a crisis is the month when the index reaches its historical maximum over the 2-year window prior to the month when the crash is triggered. The beginning of the crash corresponds to the month when the CMAX intersects with a threshold. The date of trough is the month when the price index reaches its minimum. The date of recovery is the first month after the crash when the index reaches the pre-crash maximum. The magnitude of a crisis is the difference between the value of the index at its maximum and at its minimum. The length of the trough is the number of months between the date of the beginning of the crisis and the date of the trough. The length of the recovery period is the number of months for the index to return to the maximum. To avoid counting the same crisis more than once, a crisis is automatically eliminated if detected twice over a twelve month period.

					Duration of the crises			Annual returns before crises		Annual returns after crises	
Country	**Beginning of crises**	**Beginning of crash**	**Date of trough**	**Date of recovery**	**Month to trough**	**Month to recovery**	**Price decline to trough**	**One year**	**Three years**	**One year**	**Three years**
Belgium	10/2000	*09/2002*	03/2003	05/2005	29	26	46.49%	0.793%	5.09%	20.45%	22.92%
	05/2007	*06/2008*	03/2009	NA	13	NA	66.77%	27.80%	53.94%	NA	NA
Czech Republic	05/1994	*06 /1995*	07/1995	03/2004	14	105	44.98%	NA	NA	54.96%	110.25%
	11/2007	*10/2008*	03/2009	NA	11	NA	66.41%	24.03 %	109.26%	NA	NA
Denmark	10/2000	*07/2002*	02/2003	01/2005	28	23	43.83%	43.23%	59.76%	36.33%	63.48%
	10/2007	*09/2008*	03/2009	NA	17	NA	57.77%	24.80%	49.48%	NA	NA
Germany	02/2000	*09/2001*	09/2002	NA	31	NA	67.26%	55.09%	87.98%	NA	NA
	10/2000	*10/2002*	03/2003	NA	17	NA	66.86%	22.72 %	84.73%	NA	NA
	10/2007	*10/2008*	02/2009	NA	16	NA	54.48%	32.33%	76.25%	NA	NA
Ireland	06/2001	*06/2002*	03/2003	12/2005	21	33	55.13%	21.24%	31.92%	29.87%	-44.02%
	05/2007	*07/2008*	02/2009	NA	21	NA	62.17%	35.24%	87.67%	NA	NA
Greece	11/1999	*09/2001*	09/2002	NA	22	NA	62.12%	98.27%	127.53%	NA	NA
	04/2001	*03/2003*	03/2003	09/2005	23	30	55.35%	-32.64%	20.99%	16.23%	-15.53%
	10/2007	*10/2008*	02/2009	NA	16	NA	71.20%	29.20%	114.30%	NA	NA
Spain	02/2000	*08/2001*	07/2002	09/2006	29	50	33.88%	25.89%	137.22%	11.94%	-9.11%
	09/2000	*09/2002*	09/2002	07/2005	24	34	50.39%	14.95%	50.62%	16.82%	17.45%
	11/2007	*10/2008*	02/2009	NA	15	NA	51.64%	13.97%	81.29%	NA	NA
France	08/2000	*09/2001*	09/2002	NA	25	NA	38.43%	44.36%	139.14%	NA	NA
	10/2000	*10//2002*	03/2003	NA	29	NA	50.76%	30.86%	133.55%	NA	NA
	05/2007	*10/2008*	02/2009	NA	21	NA	55.72%	23.80%	66.33%	NA	NA
Italy	08/2000	*09/2001*	09/2002	NA	25	NA	55.02%	42.66%	124%	NA	NA
	10/2000	*10/2002*	03/2003	NA	29	NA	53.86%	44.27%	119.17%	NA	NA
	05/2007	*10/2008*	02/2009	NA	21	NA	62.09%	18.71%	56.96%	NA	NA
Estonia	08/1997	*06/1998*	12/1998	12/2004	16	72	81.59%	133.53%	NA	47.96%	41%
	10/1997	*07/1999*	10/1999	03/2004	24	53	67.74%	152.22%	NA	79.76%	164%
	01/2007	*06/2008*	02/2009	NA	25	NA	58.27%	52.85%	165.24%	NA	NA
Portugal	02/2000	*07/2001*	07/2002	NA	29	NA	58.03%	30.23%	140.67%	NA	NA
	08/2000	*08/2002*	03/2003	04/2007	31	65	55.80%	20.86%	59.80%	NA	NA
	07/2007	*10/2008*	02/2009	NA	29	NA	55.30%	38.99%	88.50%	NA	NA
Slovenia	06/1994	*05/1996*	07/1996	03/1998	25	20	41.67%	35.10%	NA	10.73%	6.10%
	07/2007	*02/2008*	*04/2008*	NA	9	NA	30.96%	116.20%	145.16%	NA	NA
	09/2007	*03/2009*	03/2009	NA	18	NA	70.08%	115.81%	149.90%	NA	NA
Finland	04/2000	*02/2001*	09/2001	NA	17	NA	67.48%	165.15%	195.23%	NA	NA
	06/2000	*06/2002*	07/2004	NA	49	NA	72.91%	103.58%	123.87%	NA	NA
	10/2007	*11/2008*	02/2009	NA	16	NA	67.20%	44.54%	104.05%	NA	NA
Sweden	04/2000	*08/2001*	08/2002	NA	28	NA	63.21%	84%	174.69%	NA	NA
	09/2000	*08/2002*	03/2003	04/2007	30	49	60.94%	46.35%	86.59%	NA	NA
	05/2007	*06/2008*	01/2009	NA	20	NA	75.43%	34.62%	86.16%	NA	NA
United Kingdom	08/2000	*09/2001*	09/2002	10/2007	25	61	44.22%	2.13%	29.70%	NA	NA
	10/2000	*10/2002*	03/2003	07/2007	29	52	43.87%	2.92%	32.96%	NA	NA
	05/2007	*09/2008*	02/2009	NA	21	NA	41.96%	15.68%	47.48%	NA	NA
United States	07/2000	*07/2001*	06/2002	04/2007	23	58	39.99%	14.94%	68.73%	-8.50%	NA
	08/2000	*08/2002*	08/2002	12/2006	24	52	43.24%	11.99%	51.64%	-22.46%	NA
	09/2007	*06/2008*	02/2009	NA	17	NA	52.55%	12.44%	37.08%	NA	NA

Table 3: Evaluating the performance logit model

<table>
<tr><td colspan="2"></td><td colspan="2">Model logit</td></tr>
<tr><td colspan="2"></td><td>Signal was issued</td><td>No signal was issued</td></tr>
<tr><td rowspan="2">Actual crisis</td><td>The indicator forecasts a crisis $I_{it}=1$</td><td>Crisis properly planned</td><td>Signal Missing
(Error A)</td></tr>
<tr><td>The indicator does not forecast a crisis $I_{it}=0$</td><td>False alarm
(Error B)</td><td>No crisis properly planned by the signal</td></tr>
</table>

Table 4: Results of the logit model estimation - stock market crises

This table presents the results of the logit model. The dependent variable equals 1 for the 12 months preceding crises and the crisis itself, and 0 during calm time periods. The 11 months following the crisis are excluded from the sample. The independent variables represent the volatility index (VIX), the real interest rate (INT), the year-one-year change in stock prices (RET), the Price Earnings Ratio (PER), the inflation rate (INF), the ratio domestic credit to GDP (CREDIT) and the investor sentiment ($SENT^{\perp}$). The statistics tabulated in parentheses correspond to the p-values. The sample period includes monthly data from April 1995 to June 2009. ***, **, * denote statistical significance at 1%, 5%, and 10%.

Explanatory Variables	Model 1	Model 2	Model 3
Constant	-1.145 *** (-0.003)	-2.567*** (-0.000)	-2.436*** (-0.000)
VIX	0.002 (0.241)		0.003 (0.145)
INT	-0.121* (-0.065)		-0.095** (-0.041)
RET	-2.345** (-0.021)		-2.165** (-0.029)
PER	0.031* (0.081)		0.008 (0.189)
INF	-2.625** (-0.044)		-3.198** (-0.029)
CREDIT	0.834*** (0.006)		0.543*** (0.000)
$SENT^{\perp}$		0.157** (0.031)	0.129** (0.039)
R^2 McFadden **LR stat**	0.408 (0.000)	0.082 (0.000)	0.468 (0.000)
Forecast error (%)			
Threshold 50 % Type A$^{(1)}$ Type B$^{(2)}$	 34.090 13.627	 52.227 13.278	 25.000 11.283
Threshold 25 % Type A$^{(1)}$ Type B$^{(2)}$	 27.272 20.243	 31.818 16.212	 15.909 16.283

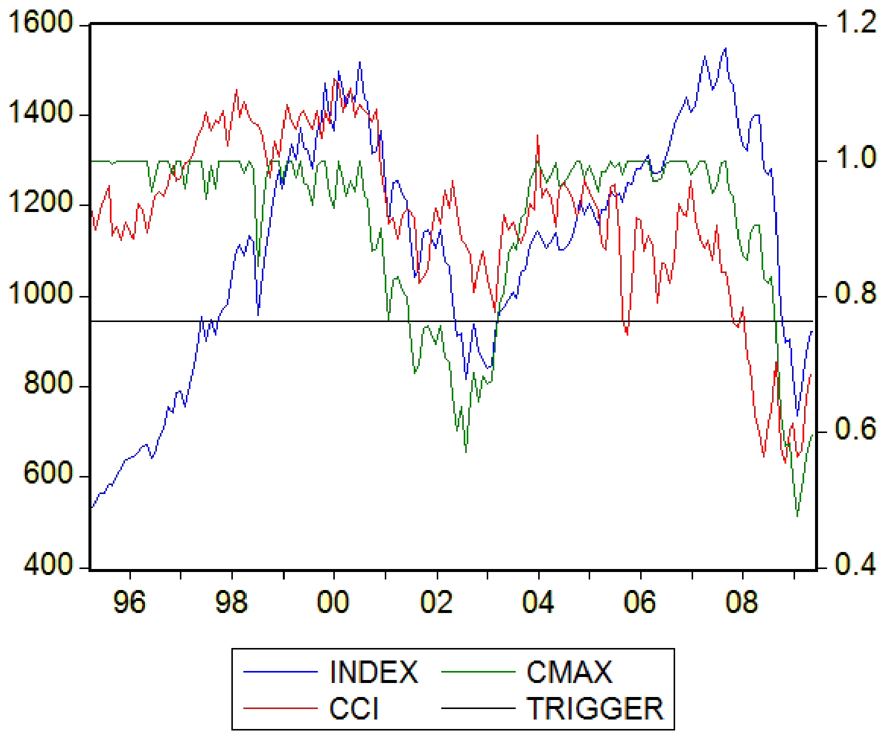
(1) Probability of crisis given no alarm.
(2) Percentage of false alarms.

Table 5: Cross sectional logit model estimation results

This table presents the results of estimating the logit model (3) when countries are pooled according to one of the determinants shown in the first column. The countries are allocated to one of two groups depending on whether they are above or below the median of a specific determinant. Sent denotes the coefficient estimated on the sentiment variable ($SENT^{\perp}$). Δ adj.R^2 is the change in adj. R^2 when the sentiment indicator is included in the logit model (3). Types A and B errors are calculated for an alert threshold of 25%. The sample period includes monthly data from April 1995 to June 2009. ***, **, * denote statistical significance at 1%, 5%, and 10%.

	Countries below median				**Countries above median**			
	Sent	**Δ adj.R^2**	**Type A**	**Type B**	**Sent**	**Δ adj.R^2**	**Type A**	**Type B**
Cultural factors								
Individualism	0.158**	0.068	0.137	0.125	0.079	0.009	0.386	0.269
Uncertainly avoidance	0.101*	0.015	0.295	0.355	0.148**	0.069	0.113	0.132
Market integrity								
Anti-director rights	0.124**	0.054	0.113	0.233	0.086	0.020	0.431	0.255
Corruption perception	0.153***	0.073	0.068	0.111	0.079	0.009	0.409	0.234
Accounting standards	0.121*	0.047	0.250	0.141	0.091	0.008	0.363	0.321

Figure 1 : US equity market index



Index refers to the S&P500, CCI to the consumer confidence index, CMAX the CMAX indicator and Trigger to the threshold set at the mean of CMAX minus two standard deviations.