

# How Does Investor Sentiment Affect Stock Market Crises? Evidence from Panel Data

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## Abstract

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, overreaction and low institutional involvement.

*Keywords:* investor sentiment, noise trader, stock market crises

*JEL Classifications:* G12, G14, G15

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## 1. Introduction

Traditional financial models have difficulty explaining financial crises. The crash of October 1987, for instance, remains enigmatic for researchers. During the crash, the Dow Jones Industrial Average 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 nonfundamental 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” (p. 129).

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 cause 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 nontrivial 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, for example, 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 investor sentiment and stock market crises remains underresearched and unresolved. Fluctuations in investors’ sentiment often are mentioned as a factor that could explain the financial crises but rarely are analyzed (De Long and Shleifer, 1991; Shiller, 2000). Few studies attempt to directly link sentiment

indicators to market crises. Only two studies are identified and both are based on the U.S. stock market crash of 1987 (Siegel 1992; Baur, Quintero, and Stevens, 1998).

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 macroeconomic 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, overreaction and low institutional development.

Our study differs 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 also are known to increase the power of statistical tests providing better estimates (Ang and Bekaert, 2007).<sup>1</sup> Third, taking an international perspective allows us to analyze 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.

## 2. Literature review

The relationship between the variables sentiment and stock returns is at odds with the 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 the result of an uninformed demand of some investors, the noise traders, and a limit to arbitrage.

The process by which security prices adjust to the release of new information also has been studied extensively. Results of these studies show that stock prices reflect more than fundamental variables. Niederhoffer (1971) highlights the weak

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<sup>1</sup> Notice, however, that due to the cross-correlations between countries, we probably have fewer than 16 independent observations per period.

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 macroeconomic variables explain approximately one-third of the variance in stock returns.

The stock market crises have led several prominent 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.<sup>2</sup>

The link between asset valuation and investor sentiment is the subject of considerable deliberations 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 measurements, the theoretical link to investor sentiment is weaker than with the direct indicators. Howe and Zhang (2011) find that investor sentiment is not an important factor in explaining seasoned equity offering volume, nor is information asymmetry.

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 sentiment measures suggested in the research. They find that the sentiment effects are stronger among stocks whose valuations are highly subjective and difficult to arbitrage. Kurov (2008) finds that sentiment investor affects traders' behavior and therefore market liquidity. He also documents that high investor sentiment has a negative effect on the transitory volatility in the futures market.

Previous studies provide evidence related to U.S. markets. Very recently, studies start to 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 United

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<sup>2</sup> On the other hand, Baur, Quintero, and Stevens (1998) 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 stock market returns when volatility factors are added (Goyal and Santa-Clara, 2003).

States, 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.

A review of previous studies highlights the lack of consensus about the best measure of sentiment or whether sentiment affects stock prices. Our paper is most closely related to Schmeling (2009) and Baker, Wurgler, and Yuan (2009) who use international data. Our study differs from theirs in that it presents original 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 include monthly observations for the period between April 1995 and June 2009. Economic data availability dictates the beginning period for most countries. As discussed below, our study includes financial and macroeconomic variables and survey results. The list of the countries and the data sources are presented in Table 1.

#### 3.1. Identification of stock market crises

The first step of our study begins by 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) design a crisis indicator called *CMAX*. The *CMAX* compares the current value of an index to its maximum value over the previous *T* periods, usually one to two years. The *CMAX* ratio is calculated by dividing the current price by the maximum price over the previous two-year period.<sup>3</sup>

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

<sup>3</sup> Similar to Mishkin and White (2002), we define a stock market crash as a 20% drop in the market over a window of 12 months, 24 months and 36 months. Findings are similar to those obtained with *CMAX*.

Table 1

**Description of variables used in the study**

Code	Variables	Measures	Sources
Macroeconomics variables			
INT	Real interest rate	Money market rate <sup>4</sup> 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 <sup>5</sup>	Domestic credit	Domestic credit divided by gross domestic product (GDP)	European Central Bank and Federal Reserve System
ST	Term spread	Difference between the yields on ten-year government bonds and three-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, nondurables goods and services consumption expenditures	Change in the natural logarithm of durable goods, nondurables and services consumption expenditures	International Financial Statistics
Stock market variables			
$P^6$	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-on-year change in stock prices	Yearly change in stock prices	Datastream
Investor sentiment indicator			
<i>SENT</i>	Consumer sentiment index	The five questions making up the consumer sentiment index	Economic European Commission and University of Michigan Survey Research Center

<sup>4</sup> Money market rate is the rate on short-term lending between financial institutions. It represents the rate on six-month interbank deposits.

<sup>5</sup> GDP quarterly data have been transformed into monthly data using moving averages. All macroeconomics time series are seasonally adjusted.

where  $P_{i,t}$  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.  $C_{MAX}$  equals one if prices rise over the period considered, indicating a bullish market. The more prices fall, the closer the  $C_{MAX}$  gets to zero. A crisis is detected each time  $C_{MAX}$  drops below a threshold set at the mean of  $C_{MAX}$  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 12-month period.

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

$$C_{i,t} = 1 \quad \text{if } C_{MAX_{i,t}} < \overline{C_{MAX}_i} - 2\sigma_i,$$

$$C_{i,t} = 0, \quad \text{otherwise.}$$

Similar to Patel and Sarkar (1998), we define the following concepts: (1) the beginning of the crisis is the month when the index reaches its historical maximum over the two-year window prior to the month when the crash is triggered; (2) the beginning of the crash corresponds to the month when the price index fell below the threshold level; (3) the date of the trough is the month when the price index reaches its minimum; (4) the date of recovery is the first month after the crash when the index reaches the pre-crash maximum; (5) the magnitude of the crisis is the difference between the value of the index at its maximum and at its minimum; (6) 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 (7) the length of the recovery period is the number of months for the index to return to the maximum.

Panel A of Figure 1 illustrates these concepts by using the U.S. stock market. As shown, three periods of crises are identified during the period 1995–2009. The first crash occurs in July 2001 and reaches a trough 11 months later in June 2002. It is characterized by a decrease of 40% in the Standard & Poor's 500 (S&P 500). The crisis ended 81 months later, in April 2007. The second crash takes place in August 2002<sup>7</sup> when the  $C_{MAX}$  drops below the threshold level. It took 52 months for the

<sup>6</sup> 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 (UK), and the S&P 500 Composite (U.S.).

<sup>7</sup> 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 or 48 months. As findings for a 12-month, 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 United States is concerned, a 20-month window identifies only two crises, 2001 and 2008.

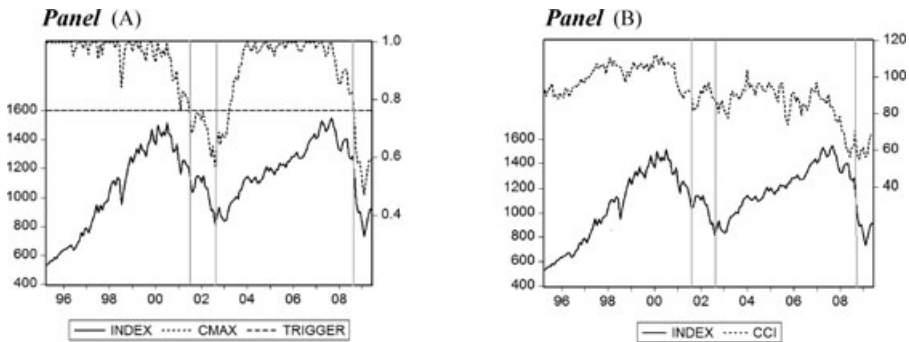


Figure 1

### S&P 500, consumer confidence index and U.S. stock market crises

The Index in (A) and (B) refers to the S&P 500 Index, 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. Vertical lines indicate the beginning of the crash.

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, for example, an average of 2.75 per country. Most of these crises correspond to well-known historical events, such as the Internet bubble of the 2000s 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%.

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

The 1970s 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 analyses and logit/probit models. Logit/probit models help to isolate “leading indicators” of financial crises.<sup>8</sup> 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, 1996; Bussiere and Fratzscher, 2006). The logit/probit models inspire our approach, outlined below.

<sup>8</sup> Discriminant analysis is not designed to determine the causes of crises, but rather to separate groups.



Table 2

**Characteristics of individual market crises**

This table presents the characteristics of the stock market crises. The beginning of the crisis is the month when the index reaches its historical maximum over the two-year window prior to the month when the crisis is triggered. The beginning of the crash corresponds to the month when the price index fell below the threshold level. The date of trough is the month when the price index reaches its minimum. The date of recovery is the first month after the crisis when the index reaches the pre-crisis 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 12-month period.

Country	Beginning of crises	Beginning of crash	Date of trough	Date of recovery	Duration of the crises			Annual returns before crises			Annual returns after crises		
					Month to trough	Month to recovery	Price decline to trough	One year	Three years	One year	Three years	One year	Three years
Belgium	10/2000	09/2002	03/2003	05/2005	29	26	46.49%	0.79%	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		

(Continued)

Table 2 (continued)  
**Characteristics of individual market crises**

Country	Beginning of crises	Beginning of crash	Date of trough	Date of recovery	Duration of the crises				Annual returns before crises			Annual returns after crises		
					Month to trough	Month to recovery	Price decline to trough	One year	Three years	One year	Three years	One year	Three years	
														Month to recovery
Germany	02/2000	09/2001	09/2002	NA	31	NA	67.26%	55.09%	87.98%	NA	NA	NA	NA	
	10/2000	10/2002	03/2003	NA	17	NA	66.86%	22.72%	84.73%	NA	NA	NA	NA	
	10/2007	10/2008	02/2009	NA	16	NA	54.48%	32.33%	76.25%	NA	NA	NA	NA	
Ireland	06/2001	06/2002	03/2003	12/2005	21	33	55.13%	21.24%	31.92%	29.87%	–44.02%	NA	NA	
	05/2007	07/2008	02/2009	NA	21	NA	62.17%	35.24%	87.67%	NA	NA	NA	NA	
Greece	11/1999	09/2001	09/2002	NA	22	NA	62.12%	98.27%	127.53%	NA	NA	NA	NA	
	04/2001	03/2003	03/2003	09/2005	23	30	55.35%	–32.64%	20.99%	16.23%	–15.53%	NA	NA	
	10/2007	10/2008	02/2009	NA	16	NA	71.20%	29.20%	114.30%	NA	NA	NA	NA	
Spain	02/2000	08/2001	07/2002	09/2006	29	50	33.88%	25.89%	137.22%	11.94%	–9.11%	NA	NA	
	09/2000	09/2002	09/2002	07/2005	24	34	50.39%	14.95%	50.62%	16.82%	17.45%	NA	NA	
	11/2007	10/2008	02/2009	NA	15	NA	51.64%	13.97%	81.29%	NA	NA	NA	NA	
France	08/2000	09/2001	09/2002	NA	25	NA	38.43%	44.36%	139.14%	NA	NA	NA	NA	
	10/2000	10/2002	03/2003	NA	29	NA	50.76%	30.86%	133.55%	NA	NA	NA	NA	
	05/2007	10/2008	02/2009	NA	21	NA	55.72%	23.80%	66.33%	NA	NA	NA	NA	
Italy	08/2000	09/2001	09/2002	NA	25	NA	55.02%	42.66%	124.00%	NA	NA	NA	NA	
	10/2000	10/2002	03/2003	NA	29	NA	53.86%	44.27%	119.17%	NA	NA	NA	NA	
	05/2007	10/2008	02/2009	NA	21	NA	62.09%	18.71%	56.96%	NA	NA	NA	NA	

(Continued)

Table 2 (continued)  
**Characteristics of individual market crises**

Country	Beginning of crises	Beginning of crash	Date of trough	Date of recovery	Duration of the crises			Annual returns before crises			Annual returns after crises		
					Month to trough	Month to recovery	Price decline to trough	One year	Three years	One year	Three years	One year	Three years
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%		
Portugal	01/2007	06/2008	02/2009	NA	25	NA	58.27%	52.85%	165.24%	NA	NA		
	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		
Finland	09/2007	03/2009	03/2009	NA	18	NA	70.08%	115.81%	149.90%	NA	NA		
	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%	84.00%	174.69%	NA	NA		
	09/2000	08/2002	03/2003	04/2007	30	49	60.94%	46.35%	86.59%	NA	NA		
United Kingdom	05/2007	06/2008	01/2009	NA	20	NA	75.43%	34.62%	86.16%	NA	NA		
	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		
United States	05/2007	09/2008	02/2009	NA	21	NA	41.96%	15.68%	47.48%	NA	NA		
	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		

### 3.2.1. 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 Bussiere and Fratzscher (2006). Using the crises identified above, we define a dummy variable  $I_{i,t}$ .  $I_{i,t}$  equals one during the crises and the 12 months preceding the crises and zero during calm 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.

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

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 also could 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 zero during calm periods, one during the crises and the 12 months preceding the crises and two during the 11 months following the crises.

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

### 3.2.2. The independent variables

The following subsections present the variables used to explain the crises detected in the sample. The first subsection introduces “traditional” variables. The second subsection 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 Coudert and Gex (2008) are the volatility index (VIX), the year-on-year change in stock prices (RET), the price-earnings ratio (PER), the inflation rate (INF), the real interest rate (INT), and the ratio domestic credit to 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 (Chicago Board Options Exchange). Coudert and Gex (2008) find that risk aversion indicators such

as VIX are leading indicators of stock market crises.<sup>9</sup> 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 U.S. data since 1789, Bordo and Wheelock (1998) show that most financial crises occurred during periods with high variation in inflation. The interest rates also are 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.

### 3.2.3. *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 macroeconomic indicators.<sup>10</sup> Second, the data on the consumer confidence index have been available for the majority of developed countries since the mid-1980s. 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

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<sup>9</sup> Coudert and Gex (2008, p.175) establish that theoretically, investor risk aversion is the same for all markets as a rational investor maximizes his expected gain by making investment choices across all types of assets. We, therefore, use the same time series of risk aversion indicator (the CBOE volatility index) for all countries.

<sup>10</sup> See Charoenruek (2006), Qiu and Welch (2006), and Lemmon and Portniaguina (2006).

purchase of durable goods. These surveys are harmonized since the mid-1980s and the questions are similar to those asked by the Survey of the University of Michigan.<sup>11</sup>

The consumer confidence index seems to be the preferred sentiment indicator of numerous researchers. Qiu and Welch (2006), 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 very highly with changes in stock prices. More importantly, Panel B of Figure 1 shows that the U.S. consumer confidence index roughly lines up with anecdotal evidence of fluctuations in sentiment. The consumer confidence index significantly 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.<sup>12</sup>

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<sup>13</sup> 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, for example, 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, for example, macroeconomic “fundamentals” ( $FUND$ ) are: (1) the changes of the industrial production (IP); (2) the growth in consumption of durables (CD), nondurables (CND) and services (CS); (3) the term spread defined as the difference in yield between the

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<sup>11</sup> Notice, however, that the European surveys ask respondents to focus on a one-year horizon while the Michigan survey asks for a one-year horizon when a household’s financial situation is concerned, but for five-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.

<sup>12</sup> Because indirect measures are made up of time series of macroeconomic and financial variables, they may not exclusively represent investors’ sentiment.

<sup>13</sup> See Brown and Cliff (2005), Kumar and Lee (2006), and Baker and Wurgler (2006).

ten-year and three-month government bonds (ST); and (4) 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 research. 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.

### 3.2.4. The model used

The dependent variable  $I_{i,t}$  or  $J_{i,t}$  are explained by the macroeconomic 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 one, we estimate the probability of a crisis within a one-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 already is challenging to predict whether or not a crisis will happen, it is difficult to determine its precise timing.

Specifically, we successively estimate three logit models per dependent variable. Model 1 includes only macroeconomic variables. Model 2 focuses on the sentiment variable. Model 3 combines macroeconomic and sentiment variables.<sup>14</sup>

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

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

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

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

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). This approach compares the probability of a crisis generated by the model, the model predicted probability, with the actual occurrence of a crisis. As the predicted probability is a

<sup>14</sup> The explanatory variables have been standardized to ensure comparability for all countries.

Table 3

**Evaluating the performance logit model**

		Model logit	
		Signal was issued	No signal was issued
Actual crisis	The indicator forecasts a crisis $I_{i,t} = 1$	Correct call of crises	Signal missing (error A)
	The indicator does not forecast a crisis $I_{i,t} = 0$	False alarm (error B)	No signal and no crisis

continuous variable, we define 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,<sup>15</sup> four situations are possible:

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 the 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 Berg and Pattillo (1999) and Coudert and Gex (2008), we decided to present the results for alert thresholds set at 25% and 50%.<sup>16</sup>

#### 4. Regression results

Our goal is to estimate the incremental predictive power of the sentiment variable compared to other variables usually used in existing studies. The findings are presented in three parts. Subsection 4.1 shows the results of a model including the fundamental economic and financial variables. Subsection 4.2 focuses on the sentiment variable. Subsection 4.3 combines economic, financial and sentiment indicators. Table 4 presents the results.

<sup>15</sup> The table is identical when  $J_{i,t}$  is used as a dependent variable.

<sup>16</sup> Notice that a robustness check using different alert thresholds do not change the performance of the models.



Table 4

**Results of the logit model estimation—stock market crises**

This table presents the results of the logit model. The dependent variable equals one for the 12 months preceding crises and the crisis itself, and zero during calm 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-on-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.

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)
McFadden $R^2$	0.408	0.082	0.468
LR stat	(0.000)	(0.000)	(0.000)
Forecast error (%)			
Threshold 50%			
Type A <sup>1</sup>	34.090	52.227	25.000
Type B <sup>2</sup>	13.627	13.278	11.283
Threshold 25%			
Type A <sup>1</sup>	27.272	31.818	15.909
Type B <sup>2</sup>	20.243	16.212	16.283

<sup>1</sup>Probability of crisis given no alarm.

<sup>2</sup>Percentage of false alarms.

LR, likelihood ratio test.

\*\*\*, \*\*, \* indicate statistical significance at the 0.01, 0.05 and 0.10 level, respectively.

#### 4.1. The predictive power of the traditional variables

With the exception of the variables VIX and INF, all macroeconomic 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 also is 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 associated with macroeconomic and financial crises, originating from macroeconomic imbalances and banking sector distress. This is why policy makers 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.<sup>17</sup> This result is different from that presented by Coudert and Gex (2008), who report that risk aversion indicators significantly increase before financial market crises. Although the VIX is considered an exogenously given measure of global risk aversion for all the countries included in the sample, our different result might be explained by the different samples of countries and by the different periods characterizing the two studies. More importantly, different results may be due to the different set of macroeconomic 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 policy makers' commitment to price stability increases the probability of a crisis. However, a negative correlation can be explained by the "paradox of credibility." Goodfriend (2001) and Borio and Lowe (2002) show that when inflation is under control, a slowdown of economic activities cannot be detected by inflation numbers but rather by instability in the financial sector.<sup>18</sup> If inflation stays low, then central banks will have no need to tighten rates and, hence, may allow financial imbalances to build up in the financial sector. The idea has been shared by the economists of the Bank for International Settlement, who have been arguing along these lines for years, finding more sympathetic ears among central bankers than among academics.

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<sup>17</sup> Results for the Global Risk Aversion Indexes (GRAI) and the Risk Aversion Index (RAI) are identical to those presented for the variable VIX. The results are not reported due to space limitation.

<sup>18</sup> The bursting of the technology bubble in the beginning of the year 2000 and the recent subprime crises took place at the end of a relatively stable period.

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. Note also that types B errors (false alarms) are relatively low for the two thresholds (13.63% 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 (13.28% 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, and 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. Stock 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 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 the 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 a 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 than the PER.<sup>19</sup>

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<sup>19</sup> 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. Qui and Welch (2006), who compare the consumer confidence index with the closed-end fund discount, also support these results.

This is a significant result, as the price-earnings ratio is frequently 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.<sup>20</sup>

Findings using the multinomial logit estimations are very similar. We find that the multinomial models do not significantly improve the predictive power of the model, both in terms of quality of regressions and quality of forecasts.<sup>21</sup> 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

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 for two periods and we compute the probability of a crisis in the following 12 months. The first subperiod ends in December 2000 and the second in December 2007. The goal is to test the model ability to predict the bear market of 2001 and the subprime crisis in 2008. The out-of-sample probabilities of logit model are summarized in Table 5.

We find that the model is performing well, even out-of-sample. It predicts most of the bear market of 2001. The model did not detect the crisis for Greece and Sweden and it anticipates crises in Slovenia and the Czech Republic that did not happened. The model also forecasts quite accurately the subprime crises occurring during the year 2008. The model failed to predict only the crisis of Denmark in September

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<sup>20</sup> 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 underestimate the probability of a stock market crisis (see Bussiere and Fratzscher, 2006, p. 960). To check the robustness of our results, we also estimate panel logit model with fixed and random effects. In both cases, the model estimates panel corrected standard errors that adjust for contemporaneous correlation and heteroskedasticity across countries. 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 on request.

<sup>21</sup> Results are available on request.

Table 5

**Out-of-sample forecasts**

This table presents the out-of-sample probabilities of the logit model estimated in Equation (3). We estimate the logit model for two subperiods. The first subperiod ends in December 2000 and the second in December 2007. We then compute the probability of a crisis in the following 12 months. A crisis is predicted when the probability of crisis is above the alert thresholds (25%).

	Out-of-sample end date: December 2000	Crises in 2001	Out-of-sample end date: December 2007	Crises in 2008
Belgium	0.198	No	0.278	06/2008
Czech Republic	0.324	No	0.266	10/2008
Denmark	0.156	No	0.191	09/2008
Germany	0.354	09/2001	0.332	10/2008
Ireland	0.167	No	0.401	07/2008
Greece	0.198	09/2001	0.312	10/2008
Spain	0.278	08/2001	0.521	10/2008
France	0.265	09/2001	0.412	10/2008
Italy	0.354	09/2001	0.598	10/2008
Estonia	0.145	No	0.365	06/2008
Portugal	0.256	07/2001	0.326	10/2008
Slovenia	0.276	No	0.456	02/2008
Finland	0.268	02/2001	0.441	11/2008
Sweden	0.154	08/2001	0.365	06/2008
United Kingdom	0.421	09/2001	0.536	09/2008
United States	0.343	07/2001	0.521	06/2008

2008. 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 a 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 also can be found in La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998), Schmeling (2009), and Chui, Titman, and Wei (2010). These variables include (1) the index of antidirector rights; (2) the corruption perception index; and (3) the accounting standards index.<sup>22</sup>

<sup>22</sup> In order to make results easier to interpret, we have rescaled all market integrity indicators. Higher value indicates higher market integrity.

Table 6

**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 ( $SENT^{\perp}$ ).  $\Delta adj.R^2$  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.

	Countries below median				Countries above median			
	$SENT$	$\Delta adj.R^2$	Type A	Type B	$SENT$	$\Delta adj.R^2$	Type A	Type B
<i>Cultural factors</i>								
Individualism	0.158**	0.068	0.137	0.125	0.079	0.009	0.386	0.269
Uncertainty avoidance	0.101*	0.015	0.295	0.355	0.148**	0.069	0.113	0.132
<i>Market integrity</i>								
Antidirector 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

\*\*\*, \*\*, \* indicate statistical significance at the 0.01, 0.05 and 0.10 level, respectively.

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 toward 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 toward more herd-like behavior. Findings are depicted in Table 6.

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 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 also have 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.

## 6. Conclusion

The general finding of a sentiment-return relation is at odds with the 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, for example, times of overly optimistic or pessimistic expectations, can persist and affect asset prices for significant periods of time, eventually generating crises. We assess the relationship between investor sentiment and stock market crises.

Specifically, our research empirically examines the influence of investor sentiment on the probability of occurrence of stock market crises during 1995–2009. We use panel data of 15 European countries and the United States to estimate a multivariate logit model. It appears that investor sentiment positively influences the probability of the occurrence of stock market crises within a one-year horizon. Furthermore, investor sentiment provides an incremental predictive power of crises compared to other variables routinely used in existing studies. 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 regulatory institutions. These results are important for portfolio managers; investor sentiment is a good predictor of securities overvaluation. Finally, these are key findings for financial market regulators because investor sentiment can be a useful way to anticipate stock market crises.

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